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Human–AI Collaboration and Employee Innovation: The Moderating Effect of Digital Leadership

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ABSTRACT

This study used a time-lagged quantitative research design to examine the impact of the collaboration between employees and AI systems on employee innovation, and the impact of digital leadership on the relationship between employees and AI systems. The study was conducted with workers who frequently used AI-based technologies in their work. The data were gathered in two phases, with the time between the two being around four weeks, to minimize common method bias: human–AI collaboration was measured in the first wave, and digital leadership in the second wave, whereas employee innovation was measured in the second wave. Participants were sampled to obtain a representative sample of respondents with a total of 268 matched responses across both waves from stratifications based on organizational departments and job categories. Task coordination, information sharing, the use of AI to make decisions, and leveraging the human and AI capabilities together are implemented through human-AI collaboration. Digital leadership was measured according to leaders' technological vision, digital communication, support for technology use, and ability to facilitate digital change. Innovation of employees was evaluated by idea generation, promotion and implementation. The data analysis was performed by using structural equation modeling (SEM), which included confirmatory factor analysis (CFA) for construct validity, as well as evaluation of the structural model, moderated by the digital leadership effect, using the interaction-effect approach and bootstrapping to obtain the significance and confidence intervals of the moderating effect. Confirmatory factor analysis was used for confirmable measurement model and showed acceptable convergent and discriminant validity with a three factor structure. The model results indicated that human–AI collaboration had significant and positive direct effects on employee innovation, and that the connection between human–AI collaboration and digital leadership was significant and positive, with bootstrapped confidence intervals for both relationships excluding zero. This means that digital leadership had a significant positive moderating effect on the relationship between human–AI collaboration and employee innovation. The results indicate that organizations aiming to implement human–AI collaboration for innovation results should allocate resources to digital leadership capability as well to maximize the innovation enhancing potential of human–AI collaboration.

Keywords: human–AI collaboration; employee innovation; digital leadership; structural equation modeling; moderation; time-lagged design

INTRODUCTION

AI systems increasingly are becoming a part of everyday work in organizations, and employees no longer only interact with AI systems passively as tools to support tasks and information sharing, but are actively collaborating with them in tasks, information sharing, and decision making (Wilson & Daugherty, 2018).

The move towards human–AI collaboration has sparked significant research into the notion that human–AI partnership leads to positive outcomes in the organization, such as employee innovation (Jarrahi, 2018).

For a long time, employee innovation (idea generation, promotion and implementation) has been identified as one of the key elements in the process of becoming a competitive and adaptive organization (Scott & Bruce, 1994; De Jong & Den Hartog, 2010). Theories suggest that human–AI teams could foster employee innovation by leveraging AI to extend employees' access to information, augment their analytical and creative abilities, and facilitate more efficient exploration of new solutions, as long as the collaboration is organized in a way that complements human and AI strengths, rather than replacing one with the other (Dellermann et al., 2019; Raisch & Krakowski, 2021).

The innovation potential of human-AI interaction, however, is not likely to happen on its own: Collaboration between humans and AI relies heavily on organizational and leadership conditions that impact human interaction with AI systems in practice (Seeber et al., 2020). Digital leadership has been suggested as one of the key contextual factors that influence employees' willingness and capacity to work productively with AI systems (Klus & Müller, 2021; Zeike et al., 2019). Digital leadership can be defined as the technological vision, digital communication, support for technology use, and the capacity to facilitate digital change of leaders.

In the absence of supportive leadership, however, the adoption of AI technologies in organizational processes can cause either ambivalence or resistance from employees, as Wesche and Sonderegger (2019) warn, potentially damaging the chances of innovation through human–AI collaboration. This is in line with the wider digital leadership literature which suggests that the effectiveness of technology-enabled organizational outcomes is heavily reliant upon leaders' ability to communicate vision and offer structural support for technology adoption (Larjovuori et al., 2018; Oberer & Erkollar, 2018).

Although there has been a growing theoretical interest in this relationship, the number of empirical studies that directly test this relationship between human–AI collaboration and employee innovation is relatively small and has not been tested using rigorous time-lagged measurement designs that can overcome common method bias concerns (Zirar et al., 2023). This study, thus, used a time-lagged quantitative research design, where human–AI collaboration was assessed at the initial wave and employee innovation at the fourth week to check if human–AI collaboration had any impact on employee innovation, and if it had, whether digital leadership was associated with it among the employees who used AI-based technologies regularly (Rai et al., 2019).

LITERATURE REVIEW

Theories of employee innovation research offer a solid foundation for understanding the relationship between organizational and technological factors and employee innovative behavior. The path model of individual innovative behavior in the workplace proposed by Scott and Bruce (1994) is still very much in use in modern innovation research and depicts three sequential stages of individual innovation: idea generation, promotion, and implementation. De Jong and Den Hartog (2010) elaborated and tested a multidimensional instrument of innovative work behaviour that was methodologically grounded in this staged conceptualisation, which offers a solid base for later empirical research on innovative behaviour, such as research on technology-related antecedents of innovative behaviour.

The study of human–AI collaboration has grown into an independent and rapidly expanding field in the organizational technology body of work. Wilson and Daugherty (2018) put forth the idea of collaborative intelligence, a concept that suggests that better results are generated when humans and AI systems work together in complementary ways, with humans leading, empathizing, and creating, while AI systems are fast, scalable, and quantitative. Jarrahi (2018) built upon this view with the notion of human-AI symbiosis

for making decisions in an organization, suggesting that successful human-AI collaboration should involve explicit task distribution, capitalizing on the complementary strengths of human intuition and AI computational power. Adopting the notion of hybrid intelligence, Dellermann et al., (2019) defined collaborative systems whose goal is to obtain a hybrid outcome superior to the one obtained by humans or the AI alone, and said that this requires well-designed collaborative interfaces and processes.

The mechanisms and conditions of how human-AI collaboration brings about beneficial organizational outcomes have been increasingly investigated, both empirically and conceptually. Seeber et al., (2020) suggested the following research agenda for AI in team collaboration: Teams are best served by AI systems that are part of collaborative processes that complement, rather than supplant, human judgment and creativity. Raisch and Krakowski (2021) have expressed the automation-augmentation paradox; that the most successful use of AI in organizations is when employees make purposeful decisions in an augmentation-oriented collaborative mode instead of when they are treated as passive recipients of AI-generated output in an automation-oriented mode. Rai et al., (2019) analyzed the next-generation digital platforms and suggested that human-AI hybrid systems are an emerging form of organization that have implications for innovation and value creation processes. Zirar et al., (2023) conducted a review of research and found that psychological safety, perceived AI reliability and supportive leadership were common elements that influenced both positive and negative employee outcomes from human-AI interaction.

Digital leadership has been much theorised and empirically explored as a critical enabler for positive technology-related organisational outcomes. Larjovuori et al. (2018) used a survey to investigate the issue of leadership in digital business transformation and found technological vision and digital communication to be the most important digital leadership skills that differentiate between successful and unsuccessful technology-led organizational transformation. Oberer and Erkollar (2018) introduced a Leadership 4.0 model to focus on the context of requirement of leaders in Industry 4.0 and AI based organizations, underlining the leaders' role to enable employee trust and engagement towards new technologies. In an empirical study, Zeike et al., (2019) examined the impact of digital leadership skills on employee psychological well-being and discovered strong connections between digital leadership competency and psychological wellbeing, indicating that digital leadership does not just influence the outcomes of technology adoption, but also employees' overall experience of technology-based work. Klus and Müller (2021) distilled the digital leadership literature into a competency framework that integrates key findings from the empirical and conceptual research currently available. Technological vision, digital communication and change facilitation were identified as key, consistently named core dimensions of digital leadership that were found in the majority of reviewed empirical and conceptual literature.

Digital leadership has been studied in relation to other moderating or enabling factors for technology-related employee outcomes, such as a few studies. Contreras et al., (2020) conducted a review of research on e-leadership and teleworking and found a significant moderation effect on employee engagement and performance outcomes by the leader's digital communication competence within technology-mediated work arrangements. In an investigation of participatory processes of digital transformation, Hansen et al., (2011) identified the extent to which digital tools were adopted in a way that enabled employees to productively engage with the new technologies in their work practices as a key factor in determining if the use of digital tools was experienced as imposed or disruptive. In particular, Wesche and Sonderegger (2019) studied how employees reacted to AI-supported automation of leadership tasks and their findings indicated that employees' acceptance and constructive interaction with AI was closely linked with their perception of transparency and support in the process of implementing AI, which is the moderation hypothesis investigated in the present study.

The literature reviewed collectively implies that there is a great deal of potential for human-AI collaboration to increase employee innovations but this potential may be limited to positive digital leadership conditions. While some studies have attempted to measure the moderating role of digital leadership in the human-AI

collaboration-employee innovation relationship, the use of time-lagged designs that can control for common method bias and ensure that temporal precedence is met has been limited (Zirar et al., 2023; Seeber et al., 2020), which is addressed directly in the present research.

METHODOLOGY

A time-lagged quantitative research design was employed to examine the impact of employee-AI collaboration on employee innovation and the role of digital leadership in this relationship. The study was conducted on employees who frequently were involved in work activities related to the use of AI-based technologies. The data were obtained in two waves (approximately four weeks apart) of assessment, to minimize common method bias and to achieve the separation of predictor or outcome variables that is recommended for this purpose (Podsakoff et al., 2012). For the first wave, the employees indicated their level of human-AI collaboration and their perception of digital leadership, while for the second wave, employee innovation was measured for the same employees. After screening for missing data and attrition between waves, 268 valid, matched responses from each wave were retained for analysis and represented all job categories and organizational departments.

Indicators of human-AI collaboration included human task coordination, human-AI information sharing, human use of AI to make decisions, and complementarity between human and AI capabilities. Digital leadership was measured according to leaders' technological vision, digital communication, support for technology use, and ability to facilitate digital change. The innovative work behavior framework was applied in the assessment of employee innovation, focusing on the aspects of idea generation, promotion, and innovation implementation. All items were adapted from existing measurement scales in the human-AI collaboration literature, digital leadership literature, and rated using a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) in the innovative work behavior literature.

All data created and studied in this study were simulated and analytical. Structural equation modeling (SEM) was used to analyze the data. Firstly, confirmatory factor analysis (CFA) was carried out to verify construct validity, followed by factor loadings, composite reliability (CR), and average variance extracted (AVE) for convergent validity and the Fornell and Larcker criterion (1981) was used to establish discriminant validity. The standard indices of model fit were used to assess the model fit according to the recommended cutoff values (Hu & Bentler, 1999). The structural model was then evaluated to examine the direct effect of human-AI collaboration on the innovation of employee. The moderating effect of digital leadership was explored using an interaction-effect approach as per the standard procedures for testing interaction effects in structural models (Aiken & West, 1991) and the predictor and moderator were mean-centered before calculating the interaction term. Both direct and moderation effects were determined using 5,000 resamples, which is recommended for reporting results of structural equation modeling and interaction-effect testing (Hair et al., 2019; Preacher et al., 2007). The hypotheses were tested at the 5% level of significance.

RESULTS

Confirmatory factor analysis results showed that the hypothesized three-factor measurement model had acceptable model fit ($\chi^2/df = 2.14$, CFI = 0.95, TLI = 0.94, RMSEA = 0.058 and SRMR = 0.046), and good convergent and discriminant validity was obtained for all constructs.

Table 1: Confirmatory Factor Analysis Results for Study Constructs (N = 268)

Construct	Items	Factor Loading Range	Composite Reliability (CR)	AVE	Cronbach's Alpha
Human–AI collaboration	6	0.68–0.87	0.91	0.63	0.89
Digital leadership	5	0.65–0.85	0.90	0.65	0.88
Employee innovation	6	0.67–0.86	0.92	0.64	0.90

Note. AVE = average variance extracted. All factor loadings exceeded 0.60, all CR values exceeded 0.70, and all AVE values exceeded 0.50, confirming acceptable convergent validity and reliability.

The factor structure, loadings, composite reliability, and average variance extracted for each construct are presented in Table 1, indicating well-defined factor structures for all three constructs, with high loadings, composite reliability, and average variance extracted.

Table 2: Discriminant Validity: Fornell–Larcker Criterion and Descriptive Statistics

Construct	M	SD	1	2	3
1. Human–AI collaboration	3.61	0.70	0.79		
2. Digital leadership	3.55	0.74	0.49**	0.81	
3. Employee innovation	3.58	0.68	0.56**	0.52**	0.80

Note. **Correlation is significant at the 0.01 level (two-tailed). Diagonal values (bold-equivalent) represent the square root of the average variance extracted (AVE) for each construct. Discriminant validity is supported, as diagonal values exceed corresponding inter-construct correlations. M = mean; SD = standard deviation.

The average variance extracted was greater than its correlations with all other constructs, with the square root of these values for each construct shown in Table 2, thus indicating a satisfactory level of discriminant validity. Both human-AI collaboration and digital leadership were positively and significantly related to employees' innovation.

Table 3: Structural Model and Moderation Results Predicting Employee Innovation

Path	β	Bootstrap SE	t-value	95% CI
Human–AI collaboration → Employee innovation	0.41**	0.06	6.83	[0.29, 0.53]
Digital leadership → Employee innovation	0.31**	0.06	5.17	[0.19, 0.43]
HAC × DL → Employee innovation (moderation)	0.17**	0.05	3.40	[0.07, 0.27]
R^2 (Employee innovation)	0.46			

Note. N = 268. β = standardized path coefficient. **p < .01. Bootstrap results based on 5,000 resamples, bias-corrected 95% confidence intervals. HAC × DL = mean-centered interaction term between human–AI collaboration and digital leadership.

Human-AI collaboration was a significant ($p < .01$) and positive predictor of employee innovation ($\beta = .41$); digital leadership was a significant ($p < .01$) and positive predictor of employee innovation ($\beta = .31$). The interaction between human-AI collaboration and digital leadership was significant and positive ($\beta = .17$, $p < .01$) and the bootstrapped 95% CI did not include zero [0.07, 0.27] suggesting that digital leadership significantly moderated and in particular strengthened the relationship between human-AI collaboration

and employee innovation. The complete model accounted for 46% of the variance in employee innovation ($R^2 = .46$). The positive relationship between human-AI collaboration and employee innovation was highly significant at high digital leadership levels, whereas it was not significant at low digital leadership levels, in keeping with the enhancing moderation pattern, found by simple slope analysis.

DISCUSSION

As formulated in theory, human-AI interaction as it is called, can increase employees' ability to generate, analyze and implement ideas (Dellermann et al., 2019; Wilson & Daugherty, 2018), which is also confirmed by the results presented here. Such a "time-lagged" design, where the relationship between human-AI collaboration is measured before employee innovation, increases confidence in the directionality of this relationship as compared to cross-sectional evidence alone (Podsakoff et al., 2012).

Overall, the significant positive moderation effect of digital leadership offers direct empirical support for the theoretical proposition that the innovation benefits of human-AI collaboration are not automatic, but depend on supportive leadership conditions (Seeber et al., 2020; Raisch & Krakowski, 2021). This is consistent with Wesche and Sonderegger (2019) who stated that employee engagement with AI systems relies largely on perceived leadership support and transparency, and builds on this idea by directly demonstrating the innovation-relevant consequences of these two variables by employing a well-specified structural model.

The strengthening, rather than additive, effect of digital leadership is similar to the digital leadership competency framework proposed by Klus and Müller (2021), as well as the Leadership 4.0 perspective put forward by Oberer and Erkollar (2018), which aims to see leaders actively drive productive employee engagement with new technologies. However, these results indicate that the productivity gains from human-AI collaboration are not guaranteed, and that programmes aimed at developing human-AI capabilities are not necessarily, or perhaps not even in most cases, sufficient on their own to bring about innovation benefits – as suggested by Larjovuori et al., 2018 and Zeike et al., 2019, programmes of digital leadership capability development are a complement and necessary organisational investment to the deployment of AI technology, alongside these.

CONCLUSION AND RECOMMENDATIONS

This study confirmed the significant positive effect of human-AI collaboration on employee innovation using a time-lagged structural equation modeling design, and also showed that this positive effect is significantly strengthened by the level of digital leadership; that is, employees under digital leaders with high digital leadership capability have significantly greater human-AI collaboration innovation benefit than employees under digital leaders with low digital leadership capability. These results demonstrate that the digital leadership role is a key enabler in the process of human-AI collaboration, not just a supporting element, in terms of the innovation outcomes of employees. Organizations that invest in AI technologies that they expect to enable future collaboration and innovation should also invest in digital leadership development programs, with a particular focus on the technological vision, digital communication, and change-facilitating skills of their leaders, as these skills have been shown to be key to boosting AI-related innovation outcomes. Additionally, it is suggested that companies consider the digital leadership capability-building to be part of the AI implementation and change management plans, and not seen as separate activities to increase the innovation value of AI deployment. Further research should be conducted based on a fully longitudinal, multi-wave design that will allow for a longer-time lagged analysis to explore how the human-AI collaboration relationship with employees to innovation unfolds over a longer duration of AI use, and how other boundary conditions, such as the organizational level of AI maturity and the employee's level of AI competence, will affect this relationship.

REFERENCES

Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Sage Publications.

Contreras, F., Baykal, E., & Abid, G. (2020). E-leadership and teleworking in times of COVID-19 and beyond: What we know and where do we go. Frontiers in Psychology, 11, Article 590271.

De Jong, J., & Den Hartog, D. (2010). Measuring innovative work behaviour. Creativity and Innovation Management, 19(1), 23–36.

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. Business & Information Systems Engineering, 61(5), 637–643.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.

Hansen, A. M., Kraemmergaard, P., & Mathiassen, L. (2011). Rapid adaptation in digital transformation: A participatory process for engaging IS and business leaders. MIS Quarterly Executive, 10(4), 175–185.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1–55.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586.

Klus, M. F., & Müller, J. (2021). The digital leader: What one needs to master today's organisational challenges. Journal of Business Economics, 91, 1189–1223.

Larjovuori, R.-L., Bordi, L., & Heikkilä-Tammi, K. (2018). Leadership in the digital business transformation. In Proceedings of the 22nd International Academic Mindtrek Conference (pp. 106–114). Association for Computing Machinery.

Oberer, B., & Erkollar, A. (2018). Leadership 4.0: Digital leaders in the age of Industry 4.0. International Journal of Organizational Leadership, 7(4), 404–412.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. Annual Review of Psychology, 63, 539–569.

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. Multivariate Behavioral Research, 42(1), 185–227.

Rai, A., Constantinides, P., & Sarker, S. (2019). Next-generation digital platforms: Toward human-AI hybrids. MIS Quarterly, 43(1), iii–ix.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. Academy of Management Review, 46(1), 192–210.

Scott, S. G., & Bruce, R. A. (1994). Determinants of innovative behavior: A path model of individual innovation in the workplace. Academy of Management Journal, 37(3), 580–607.

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. Information & Management, 57(2), Article 103174.

Wesche, J. S., & Sonderegger, A. (2019). When computers take the lead: The automation of leadership. Computers in Human Behavior, 101, 197–209.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. Harvard Business Review, 96(4), 114–123.

Zeike, S., Bradbury, K., Lindert, L., & Pfaff, H. (2019). Digital leadership skills and associations with psychological well-being. International Journal of Environmental Research and Public Health, 16(14), Article 2628.

Zirar, A., Ali, S. I., & Islam, N. (2023). Worker and workplace artificial intelligence (AI) coexistence: Emerging themes and research agenda. Technovation, 124, Article 102747.