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Human–AI Collaboration and Innovative Work Behavior: Examining the Mediating Role of Job Satisfaction

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ABSTRACT

This study aims to explore the impact of Human–AI Collaboration on the Innovation Behavior of employees in the banking sector, focusing on the mediation effect of Job Satisfaction and the moderation effect of AI Self-Efficacy. The study draws its concept of Human–AI Collaboration from the Job Demands–Resources (JD–R) Theory, which considers HACC as a strategic organizational resource that can boost employees' motivation and innovative performance. Quantitative, Cross Sectional. A quantitative, cross-sectional research design was used. Structured questionnaires were used to gather data on 384 employees of commercial banks who have experienced the use of AI in their work. To ensure the respondents had the relevant work experience with AI, purposive sampling was used and explore the direct, mediating, and moderating relationships, the proposed conceptual model was analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique by SmartPLS 4. The results show that Human–AI Collaboration has a significant positive impact on Job Satisfaction and Innovation Behavior. Job Satisfaction positively impacts Innovation Behavior and partially mediates the link between Human–AI Collaboration and Innovation Behavior, suggesting that a collaborative environment with AI can foster innovation by enhancing employee work satisfaction. The findings of this study could help bank executives, human resource managers, and policymakers understand the importance of human-focused implementation of AI, ongoing AI skill-building, and favorable organizational practices that boost employee satisfaction and innovation. To truly unlock the strategic benefits of Human–AI Collaboration, organizations must include investment in employee capability development within their AI investments. This study adds to the growing increasingly relevant literature on Human–AI Collaboration by combining technological and psychological aspects in one framework. It expands on the JD–R Theory by clarifying the strategic role of Human–AI Collaboration as a job resource that fosters innovation by Job Satisfaction, and shows the contingent role of AI Self-Efficacy in AI-enabled workplaces.

Introduction

Artificial intelligence (AI) has become one of the most impactful technologies driving the banking sector towards a new era. Machine learning, natural language processing, generative AI and predictive analysis are redefining the way banks are serving their customers, handling risk, preventing fraud, disbursing loans, and much more. Instead of displacing human staff, modern banking organizations are turning to Human–AI collaboration, a strategy that empowers AI to augment employees' cognitive function and enables them to add context, judgment, ethics, creativity, and relationship management (Sweiss & Yamin, 2024). This collaborative model understands that better organizational results are achieved not only through automation, but through the use of intelligent technologies and human expertise combined. This has led to a significant focus on the adoption of AI tools in banking, particularly in creating AI-enhanced work environments where humans and AI collaborate on intricate business operations and strategic decisions (Rulandari & Silalahi, 2025). As a result, banks around the globe are investing heavily in AI-driven workplaces where employees and AI systems work side by side to execute complex operational and strategic processes. The recent emergence of generative AI in large-scale deployments in financial services institutions are all good examples of collaborative intelligence becoming a strategic imperative to support productivity and service innovation (Fan et al., 2025).

Banking stands out as a particularly interesting field for analyzing Human–AI collaboration, as it demands analytical accuracy, adherence to regulations, trust from customers and human judgment. The applications of AI in the finance sector span across diverse areas, including credit analysis, fraud prevention, investment advising, customer service, compliance oversight, and customized financial advice. But the best examples of AI use have been where it has complemented human knowledge and skills. While full automation might limit flexibility and miss the context, a collaborative decision-making process between humans and AI can enhance decision-making quality and organizational resilience. For instance, in financial underwriting, AI-driven recommendations have been shown to complement human expertise, resulting in more accurate and consistent loan decisions compared to using AI or manual methods alone (M. Chen et al., 2026). In an era when banking operations are increasingly digital, innovation is a key factor in determining the competitive advantage. Banks are constantly required to create new products and services, optimize operations, optimize customer experience, and adapt quickly to new market trends and needs. Staff are thus vital in creating, advocating and implementing innovative ideas. Innovation behavior is the act by employees of deliberately engaging in activities that will result in new products or ideas that will enhance the effectiveness of the organization.

AI gives employees unparalleled access to information, prediction, and analytical capabilities, but ultimately the innovation must be created through the willingness of employees to experiment, solve problems creatively, and work across organizational lines (Wu et al., 2024). These creative behaviors could be further boosted by human–AI collaboration through the reduction of routine tasks, increased knowledge accessibility, and increased time allotted to creative and strategic tasks. There is growing evidence that effectively designed Human–AI collaboration increases financial organizations' innovation capability and managerial performance (Ji et al., 2025). While the technology component of innovation is important, the technological ability alone does not explain successful innovation. The human factor is still a crucial part in understanding if employees will adopt AI and use it to its full potential. One of these factors, job satisfaction, plays an important role as it is well established that a satisfied employee is a more motivated, engaged, committed, and contributor beyond the call of duty. When humans and AI work together, it can increase employees' sense of competence, improve their decision quality, help in learning, and even reduce repetitive work, which can enhance job satisfaction. On the other hand, AI systems that are poorly designed could create technostress, uncertainty, perceived job insecurity, and dissatisfaction. Hence, the work style of the employee will be a key determinant in how effective AI is. The importance of maintaining a significant human role in AI-driven tasks is highlighted by recent studies, which show that this balance improves employee satisfaction and performance, while also fostering creativity (Liu & Li, 2025).

Employees' job satisfaction is also highly correlated with their innovation behaviors. Positive employee attitudes toward work engender greater willingness to share knowledge, try new ideas, creatively solve organizational problems, and share innovative ideas. Happy workers are more likely to feel committed to the company, to be more motivated internally, and to be willing to put in extra effort for the company on innovation-related tasks. Job satisfaction can then serve as a crucial psychological process by which Human–AI collaboration can lead to creative results in AI-enabled workplaces. Positive attitudes of employees toward AI will foster innovative work behavior if they see AI as a supportive tool rather than a threat. From this point of view, technological investments are not enough to ensure innovation unless employees are made to be happy in environments supported by technology related to artificial intelligence (Agaoglu et al., 2025).

While the Human–AI collaboration has received increased scholarly interest, there are some significant gaps in the literature. First, the studies are oriented towards examining AI adoption, operational efficiency, automation, and technology acceptance, with few studies looking at the Human–AI collaboration as a shared organizational capability that affects employee innovation. Second, existing bank research has concentrated mostly on the customer's experience, fraud detection, credit analysis, and service automation, but few studies address employees' behaviors. Third, the Employee attitudes between Human–AI collaboration and innovation behavior is still under-researched, especially in the banking sector. The evidence also shows that organizational culture, employee skill levels and collaborative work design are important factors in the successful implementation of AI, which means that more comprehensive behavioral models are needed that combine both technological and psychological aspects (Gao et al., 2026).

This study is interested in the gaps as it investigates the effects of Human–AI collaboration on the innovation behavior of employees in the banking sector, with job satisfaction as the mediating variable. The study is based on the Job Demands – Resources (JD–R) Theory, which conceptualizes Human–AI collaboration as a valuable job resource that contributes to the enhancement of employees' work experiences through cognitive support, task efficiency and informed decision making. These resources raise job satisfaction, and job satisfaction, in turn, promotes employees' innovative work behaviors (B. Wang et al., 2026). This theoretical stance offers a broad understanding of the potential of technological resources to impact on psychological states and consequently organizational outcomes.

The study makes some significant contributions to theory and practice. It is hoped that it builds on the current Human–AI collaboration literature and combines the technological capabilities and employee attitudes and innovation behaviors in a unified framework. It further extends the JD–R theory by showing how collaboration enabled by AI can be regarded as a strategic resource for an organization, which can lead to more job satisfaction and consequently employee innovation. In practice, the results will offer banking executives, HR managers, and digital transformation leaders valuable evidence-based insights to create AI-supported workplaces that are more efficient and also more satisfying to employees and more innovative. In an era of banks that are still on the cutting edge of generative AI and intelligent decision-support systems, the human factors of AI collaboration will only grow in importance to ensure sustainable competitive advantage in the digital financial landscape.

Literature Review and Hypotheses Development

The power of Human–AI collaboration is not only a technology implementation problem, but also a strategic organizational capability, as noted in the literature in recent years. Artificial Intelligence (AI) is no longer just about automation; it's about enhancing human intelligence in decision-making, creativity, and innovation in contemporary organizations. In the banking sector, for instance, digital transformation, rising customer expectations, regulatory intricacies, and the need to compete with other financial institutions are driving a surge in AI system investments. New applications include complex tasks like credit evaluation, fraud detection, risk assessment, customer relationship management, investment advisory, and compliance monitoring, where human workers are now collaborating with AI systems. Therefore, it is imperative to investigate How-Human–AI collaboration affects employees' attitudes and behaviors, making this a key research priority.

Human–AI Collaboration

Human-AI collaboration is a working model in which humans and AI systems work together to perform a job to the best of their combined abilities and resources, rather than one working alone. Collaborative AI prioritizes collaboration over replacement, unlike traditional automation. AI adds the computational power, pattern recognition, predictive analysis, and data manipulation, while humans bring the context, ethical considerations, emotional intelligence, creativity and strategic thinking. Together, this intelligence enables organizations to optimize productivity and get the best of human resources. Effective collaboration between Human and AI relies on factors beyond just technology, such as trust, transparency, user control and organizational support, as highlighted in recent reviews (A. Chen et al., 2023). With the rise of generative AI, the Human–AI collaboration has also changed. Today AI systems can be used to create reports, summarize financial data, suggest strategic moves, manage customer interactions, and aid management decisions in real-time. AI assistants are becoming more common in financial institutions, working alongside human staff to enhance their productivity, but not taking their place. New research in the finance industry shows that by combining competencies of the employees, intelligent systems that employees can trust, good data quality within the organization, and sound management, the Human–AI collaboration can positively influence innovation capability and managerial performance. Human-AI collaboration is a reality in the banking sector worldwide. Banks are increasingly using AI-powered digital assistants to assist customer service representatives, fraud analysts, loan officers and investment professionals. This has been seen with the adoption of generative AI in customer service chatbots and employee support systems by major global banks, which is helping to boost productivity, cut down on response times, and enhance customer experiences. The developments reflect a wider shift that is going on, toward a new level of collaborative intelligence, where the power of AI is used to supplement, rather than supplant, human efforts (Kong et al., 2024). While all these advances have been made, Human – AI collaboration also poses organizational struggles. If AI systems are overly aggressive or intrusive into decision-making, they can make employees feel like they have less control or ability to make their own choices. Experimental results show that AI agents that are very proactive can lower users' competence-based self-esteem and make them less satisfied with the AI system, especially those with more AI knowledge. Organizations need to thoughtfully integrate AI automation with human involvement to ensure positive employee experiences and make sure it doesn't replace human judgment (Sun et al., 2026).

H1: Human–AI Collaboration positively influences Job Satisfaction.

The Role of Job Satisfaction in AI-Enhanced Workplaces

One of the most well-researched employee attitudes studied in organizational behavior research is job satisfaction. It is the total subjective assessment of employees' experiences in the workplace and is a measure of whether work meets employees' expectations, needs and career aspirations. In AI-infused work environments, job satisfaction has reemerged as an essential measure, underscoring how the introduction of AI is reshaping how people work, the nature of their tasks, and their experiences in the workplace. There are several ways human-AI collaboration can impact job satisfaction. AI systems minimize repetitive administrative tasks, enhance information accessibility, speed up decision-making and assist workers in handling intricate challenges. This improvement can help to boost competence, autonomy, and work meaningfulness perceptions, which may boost job satisfaction. On the other hand, if AI is not implemented well, it can create uncertainty, technostress, job insecurity, concerns about algorithmic monitoring, and a sense of threats to professional identity, which can ultimately decrease employee satisfaction. Thus, the impact of collaborative AI adoption on employees' working environments depends on what they experience. In this way, the outcomes of collaborative AI adoption in the workplace are either positive or negative for employees (Shi et al., 2026).

Recent research has repeatedly shown that it is crucial to build AI systems that maintain employee autonomy and support workers' collaboration. Human-centered AI views help companies to engage in human decision-making processes when implementing AI, to train their staff, to explain the AI recommendations, and to keep the human in control of decisions that are crucial to the company. Such practices enhance confidence in AI systems and foster a positive attitude and acceptance of technology within the workspace (Wu et al., 2025).

In financial institutions, employee satisfaction has gained in significance due to the changing technological landscape, the orientation on customers and the high level of regulation of the professional role of bank employees. By streamlining operations and enabling workers to concentrate on more high-value tasks like customer relationship management, financial counseling, and strategic problem-solving, AI-driven workplaces can increase staff satisfaction. But with all efforts towards automation and job loss by employees, financial institutions have also to take measures to ensure the positive attitudes of employees (Wu et al., 2025).

H2: AI Self-Efficacy positively moderates the relationship between Human–AI Collaboration and Job Satisfaction, such that the relationship is stronger when AI Self-Efficacy is high.

Innovation Behavior

Innovation behavior is defined as the deliberate actions taken by employees to produce, stimulate and implement new ideas that enhance the performance of an organization. Creativity is mainly about the process of idea generation, while Innovation behavior includes the entire process, from perceiving opportunities to successfully introducing new solutions into organizations. Innovation behavior helps to enhance customers' services, optimize operational processes, launch new financial products and secure sustainable competitive advantage in the banking industry. The digitalization of banking has greatly broadened employees' opportunities to work innovatively. Advanced analytical tools, predictive capabilities, real-time information, and automated knowledge management systems powered by AI empower employees with sophisticated analytical capabilities, predictive insights, real-time information, and automated knowledge management systems, fostering creative problem-solving. AI is not about replacing human innovation, but often it is a cognitive assistant that amplifies employee ingenuity to uncover possibilities and create innovative solutions. Empirical studies in recent years indicate that the use of AI has both enabling and limiting impacts on innovation behavior (Jacob & Kumar, 2026). The Job Demands–Resources (JD–R) theory suggests that AI can serve as both a job resource and a job demand. Researchers suggest that AI can be seen as a job resource as well as a job demand, as per the Job Demands–Resources (JD–R) theory. AI can be used as a resource to boost the positive motivation, learning opportunities, and innovativeness of employees. AI can also add to job insecurity and technological pressure as a demand, hindering innovation. The dual effects suggest that while organizations can leverage AI to foster innovation, they also need to be mindful of its potential negative psychological impact and manage it accordingly (Kong et al., 2024).

In the banking context, innovative work behavior is especially significant, particularly due to the many regulatory pressures, cyber security threats, fintech competitors and customer expectations that financial services institutions are constantly experiencing. The results of the studies conducted among banking employees show that variables such as job embeddedness, support of leaders, organizational commitment have a significant positive impact on encouraging innovation behavior. Likewise, too much technostress as a part of digital transformation can have a negative impact on innovative performance without leadership and resources supporting the process to change (Rostamzadeh et al., 2025).

How can people collaborate with AI and how does it affect their innovation practices?

The literature is growing in the positive association between Human-AI collaboration and innovation behavior. By leveraging collaborative AI, workers can focus more on creative work, as repetitive tasks are automated and AI delivers intelligent decision support. Human workers then use their know-how to assess AI-generated insights, create new solutions and introduce new enhancements. Human-centered collaboration is then a situation that enables technological intelligence to support human creativity. Empowerment of employee capabilities, trusted AI systems and good quality data within financial organizations can positively influence the level of innovation capability and managerial performance if humans are part of the equation. Likewise, studies about the collaboration between employees and AI suggest that AI can help decrease workload and inspire employees to take proactive actions that can lead to innovation (Li & Zong, 2026).

H3: Job Satisfaction positively influences Innovation Behavior.

Job satisfaction as the mediator of job performance and career success

Even though there have been studies that have highlighted the significance of Human–AI collaboration and innovation, there has been comparatively less effort in terms of explaining the psychological mechanisms linking these variables. Job satisfaction is an especially pertinent mediator as happy workers tend to be more intrinsically motivated, committed to the organization, knowledge sharing, and willing to provide innovative ideas. Human–AI collaboration is a significant job resource for the Job Demands–Resources (JD–R) Theory, as it adds to the positive aspects of employees' work experiences by increasing efficiency, decreasing routine workload, and aiding decision making. The positive work experiences enhance job satisfaction, which then encourages workers to put more effort into innovation actions. So, job satisfaction offers a theoretically sound explanation of the final impact of collaborative AI on innovation behavior (Y. Wang et al., 2025). Although the research on Human–AI collaboration has been rapidly expanding, empirical studies investigating the mediation of job satisfaction in the banking sector are still limited. Existing banking research has focused mainly on the customer experience, operational efficiency, fraud prevention and the use of AI, with less research focused on outcomes for employees (Li & Zong, 2026). This is especially crucial as the effectiveness of AI in the long run is as much about employee collaboration with AI systems as it is about technological capabilities, and the ability to convert this collaboration into creative organizational results. Based on this, this study aims to contribute to the existing knowledge on Human–AI collaboration and its effect on employees' innovation behavior by proposing that this relationship is mediated by improving their job satisfaction (Verma & Singh, 2022).

H4: Human–AI Collaboration positively influences Innovation Behavior.

Theoretical Framework

This study builds on the Job Demands–Resources (JD–R) Theory proposed by (Bakker & Demerouti, 2007). The JD–R theory offers a complete framework for explaining the relationships between employees' psychological well-being, their motivation, and their performance as a result of their workplace resources and job demands. The theory suggests that for each occupation there are certain job demands and job resources. Job demands are the physical, psychological, social or organizational requirements of the job that require continued effort that can cause stress when presented in excess. Job resources, on the other hand, are those elements of the job that assist employees to reach their job goals, minimize job demands, stimulate personal development, and boost motivation. The theory proposes that, if organizations make adequate resources available, staff become more engaged, more satisfied and able to show positive outcomes in the workplace, such as innovation. The uploaded manuscript clearly positions human–AI collaboration as a valuable job resource that will improve employees' work experiences with its cognitive support, task efficiency and informed decision making. As a component of the banking sector, Human–AI Collaboration is a valuable organizational resource as AI systems support the decision-making process, automate repetitive tasks, enable knowledge sharing, and offer intelligent suggestions to employees. AI is not a substitute for humans; it augments their abilities so that people can concentrate on more strategic, creative, and customer-facing tasks. These technological resources decrease routine workload and increase employees' perceptions of competence, autonomy and effectiveness in the JD-D perspective. This results in happier workers due to the efficiency and confidence that AI allows them to operate their roles. The manuscript also shows that while there can be technostress and uncertainty introduced by the use of poorly implemented AI, the primary way in which Human–AI Collaboration proves to be a motivator is to create positive employee attitudes. The theory also posits that when there is higher job satisfaction, there is higher investment of cognitive and affective resources into the job. Happy workers are ready to put in new ideas, share information, creatively resolve work problems, and apply innovative solutions. Thus, job satisfaction is considered to be an important psychological mechanism that links human–AI collaboration and employees' innovation behavior. In the JD–R context, the collaboration between human and AI first improves employee experiences at work and their motivation, which then benefits the innovative behavior of employees. The mediating effect of job satisfaction has been a focal point in the translation of the technological resources to valuable organizational outcomes.

The proposed framework also includes AI self-efficacy as a moderating variable. AI self-efficacy is the level of confidence that employees have in their understanding, learning, and ability to effectively use AI technologies in the workplace. Higher AI self-efficacy allows employees to better use AI systems, understand the significance of the AI-recommended actions and apply AI in decision-making. AI self-efficacy can be viewed from the JD–R perspective as a personal resource that enhances the positive effects of organizational resources on employee outcomes. Employees with greater AI Self-Efficacy are more likely to benefit from Human–AI Collaboration, and experience higher levels of job satisfaction than those with lower AI Self-Efficacy. Therefore, AI self-efficacy amplifies the motivational process suggested by the JD–R theory by boosting the capacity of the employees to make the technological resources produce positive working experiences. In general, the JD–R theory offers a solid theoretical basis for the proposed research model and how it relates to the concepts of Human–AI Collaboration, Job Satisfaction, AI Self-Efficacy, and Innovation Behavior. The theory builds upon the idea that human–AI collaboration is a strategic job resource that leads to employee satisfaction, and that AI self-efficacy improves human-AI collaboration. Higher job satisfaction then leads to higher motivation among employees to perform innovative work behavior, which involves the initiation, promotion and implementation of new ideas in banking organizations. Hence, the JD–R model provides a thorough understanding of the roles of AI in enhancing employee attitudes and innovation, and in sustaining organizational performance in the banking context.

Methodology

Research Design

The study used an exploratory research design with a quantitative and cross-sectional approach to investigate the relationships between Human–AI Collaboration, Job Satisfaction, AI Self-Efficacy and Innovation Behavior in the context of the banking industry. A quantitative approach was suitable since it allowed the latent constructs to be empirically tested for hypothesized relationships with statistical tools. The cross-sectional design was used to gather data at one specific time from banking employees to assess their perceptions of the use of AI-supported work environments and its effects on their innovation behavior.

The proposed conceptual model was tested using the software of Partial Least Squares Structural Equations Modeling (PLS-SEM) by SmartPLS 4. There are some scenarios where PLS-SEM is especially appropriate, including when the study model is complex, with mediation and moderation effects, or prediction-oriented, or when the variables measured are latent variables with multiple indicators. Additionally, PLS-SEM is one of the most popular statistical analytical tools for management, information systems and organizational behavior research because of its capability of dealing with non-normal data distribution and small to medium size samples. This research was done in the banking sector because artificial intelligence in the bank sector has been gradually implemented in the operation of the organization. AI is being embraced by commercial banks in customer relationship management, fraud detection, credit risk assessment, and digital banking, as well as in customer service automation, investment advice, and regulatory compliance. The banking sector is a suitable environment to explore Human–AI Collaboration because, in everyday activities, banks' staffs inevitably have to interact with systems that use AI. The target population consisted of commercial bank full-time employees who typically use AI-assisted technologies, such as branch managers, operations management, relationship managers, customer service officers, loan officers, IT professionals, digital banking, compliance officers, risk management, and others. To ensure the participants were familiar with organizational processes and AI applications, at least one year's work experience of their employees was considered.

Sampling Technique and Sample Size

A purposive sampling technique was used in this study as it focused on employees with first-hand experience of using AI-enabled technologies in their work. Purposive sampling enables researchers to choose the respondents who have the knowledge and experience to be able to give valuable information about Human–AI Collaboration. A total of about 450 structured questionnaires were sent to the employees of the selected commercial banks. The number of questionnaires collected was about 384 valid questionnaires which is the expected sample size for statistical analysis once the questionnaires that were incomplete and could not be used were excluded. PLS-SEM is a method that requires a sample size larger than the minimum size required according to the model complexity, as stated by (Hair & Alamer, 2022). As a result, the suggested sample size is adequate to test for direct, mediating and moderating relationships.

Data Collection Procedure

Structured self-administered questionnaires were used to gather primary data. Permission was secured (where necessary) from the banking institutions that participated in data collection prior to the start of data collection. Participants were explained the academic objectives of the research and were guaranteed of voluntary participation. Questionnaires were issued both in hard copy and electronically as per the preference of participating banks. Participants were given detailed information about how to complete the questionnaire and that there was no right or wrong answers. The study ensured confidentiality and anonymity of participants and did not collect any personally identifiable data. Data collection took about 8-10 weeks, which provided enough time for employees to fill out the questionnaire.

Measurement of Variables

All constructs were assessed with previously validated scales taken from existing literature. Some minor wording changes were made to make the measurement items consistent with the banking context, but retain the meaning of the items. Answers were taken on a five-point Likert scale: 1 = Strongly Disagree and 5 = Strongly Agree.

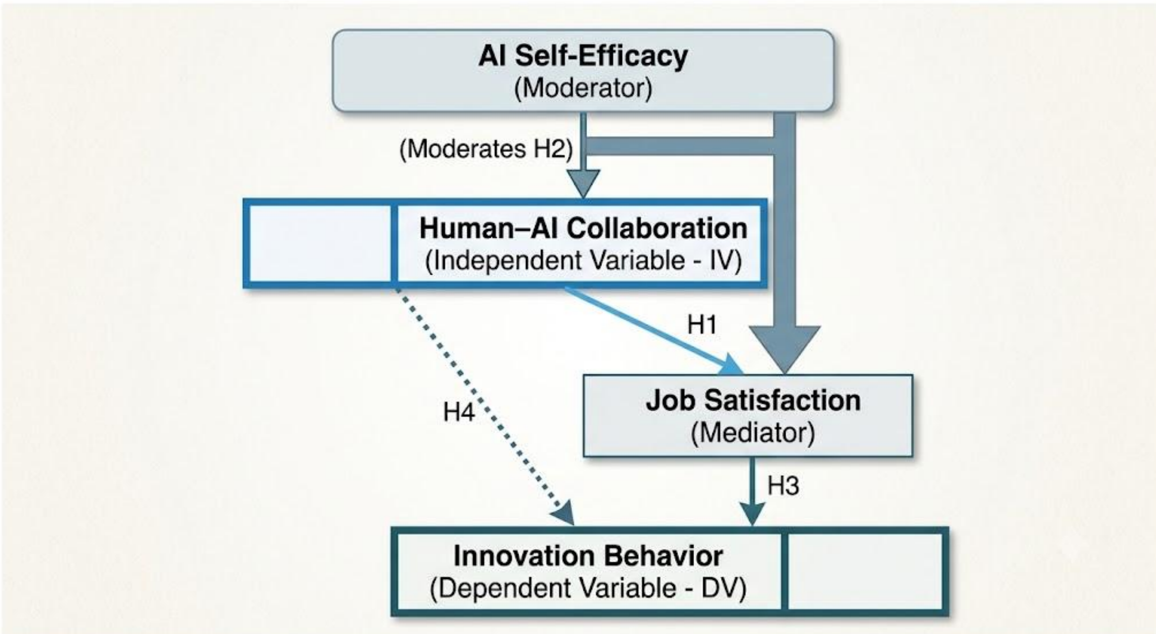

Fig. 1 Conceptual framework of the study showing direct and mediating relationships

Human–AI Collaboration

The Human–AI Collaboration was assessed by 7 items adapted from previous research on collaborative intelligence and human–AI team collaboration (Dellermann et al., 2019; Seeber et al., 2020). The scale assessed the perceptions of the employees about the use of AI in decision making, group problem-solving, knowledge sharing, and AI support in job tasks.

Sample item: “AI systems help me a lot to make decisions in my work.”

Job Satisfaction

Five items adapted from the scale developed by (Brayfield & Rothe, 1951) and used in organizational behavior research were used to assess Job Satisfaction. The instrument assessed the overall satisfaction of the employees toward their work, work environment, and organizational experience.

Sample item: Overall I am happy with my present situation.

AI Self-Efficacy

Five items from computer self-efficacy and AI capability literature were used to measure AI Self-Efficacy. The construct assessed employees' confidence in learning, understanding, and effectively utilizing AI technologies to accomplish work-related tasks.

Sample item: I have confidence in my understanding of using AI technologies to effectively complete my job.

Innovation Behavior

Nine items adapted from (Janssen, 2000) were used as indicators of Innovation Behavior. The instrument recorded the employees' behaviors on the areas of idea generation, idea promotion and idea implementation inside the organization.

Sample item: I regularly make new and creative ideas to enhance ways of doing things at work.

Pilot Study

A pilot study consisting of 30 banking staff was conducted to check the clarity, readability and reliability of the questionnaires before the main study. Some wording changes in the items were made to improve the understanding of the items after feedback from the participants. The results of preliminary reliability analysis showed that all constructs had satisfactory internal consistency, with Cronbach's alpha values above the suggested level of 0.70.

Data Analysis Technique

Data collected were analyzed with IBM SPSS Statistics and SmartPLS 4. Data screening was done using SPSS, with the following aims: identifying missing values, identifying outliers, descriptive statistics, and demographic analysis. Then, the SmartPLS 4 program was used to analyze the measurement model and structural model.

Table 1: Measurement Model Assessment Criteria

Assessment	Criterion	Recommended Threshold	Purpose
Indicator Reliability	Indicator Loadings	> 0.70	Evaluates the reliability of individual measurement items.
Internal Consistency Reliability	Cronbach's Alpha	> 0.70	Assesses the internal consistency of each construct.
Internal Consistency Reliability	Composite Reliability (CR)	> 0.70	Measures the overall reliability of latent constructs.
Convergent Validity	Average Variance Extracted (AVE)	> 0.50	Determines whether a construct explains more than 50% of the variance in its indicators.
Discriminant Validity	Fornell–Larcker Criterion	Square root of AVE should	Confirms that each construct is empirically distinct from other

		exceed inter-construct correlations	constructs.
Discriminant Validity	Heterotrait–Monotrait Ratio (HTMT)	< 0.85	Assesses discriminant validity between latent constructs.

Interpretation: The measurement model was evaluated by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. These assessment procedures ensure that the measurement scales are reliable and that each construct represents a distinct theoretical concept.

Table 2: Structural Model Assessment Criteria

Assessment	**Criterion**	**Recommended Threshold**	**Purpose**
Hypothesis Testing	Path Coefficients (β)	Significant	Examines the strength and direction of relationships among constructs.
Hypothesis Testing	t-values	> 1.96 (at 5% significance level)	Determines the statistical significance of the hypothesized relationships.
Hypothesis Testing	p-values	< 0.05	Indicates whether the proposed relationships are statistically significant.
Significance Testing	Bootstrapping	5,000 resamples	Estimates the significance and confidence intervals of path coefficients.
Explanatory Power	Coefficient of Determination (R^2)	0.25 = Weak, 0.50 = Moderate, 0.75 = Substantial	Measures the variance explained in endogenous constructs.
Effect Size	Effect Size (f^2)	0.02 = Small, 0.15 = Medium, 0.35 = Large	Evaluates the contribution of each exogenous construct to the endogenous construct.
Predictive Relevance	Predictive Relevance (Q^2)	> 0	Assesses the model's predictive capability using the blindfolding procedure.
Collinearity Assessment	Variance Inflation Factor (VIF)	< 3.30 (acceptable), < 5.00 (maximum)	Detects multicollinearity among predictor constructs.

Interpretation: The structural model was assessed by examining the significance of the hypothesized relationships, explanatory power, effect sizes, predictive relevance, and multicollinearity. Statistical significance was evaluated using a **5,000-resample bootstrapping procedure** with a significance level of **$p < 0.05$**. These criteria ensure the robustness, predictive accuracy, and validity of the proposed structural model.

Mediation and Moderation Analysis

SmartPLS 4 was used to analyze the mediating role of Job Satisfaction, with the bootstrapping procedure. Both direct and indirect effects were examined to test partial or full mediation of the relationship between Human–AI Collaboration and Innovation Behavior by Job Satisfaction. An alternative method for estimating the strength of mediation was the Variance Accounted for (VAF) method. The moderating effect of AI Self-Efficacy was tested using the product indicator approach in SmartPLS 4. To investigate whether the relationship between Human–AI Collaboration and Job Satisfaction was reinforced or weakened after adding an interaction term between Human–AI Collaboration and AI Self-Efficacy. An interaction term between Human–AI Collaboration and AI Self-Efficacy was added to see if this interaction strengthened or weakened the relationship between Human–AI Collaboration and Job Satisfaction.

Ethical Considerations

Research was conducted in an ethical manner. All participants were voluntary, and were provided with information about the goals of the study prior to completion of the questionnaire. The participants gave informed consent and were informed that their answers were anonymous and confidential. The data were only used for academic research purposes, and that they were securely stored to ensure that they were not accessible to those other than authorized. The participants had the right to drop out of the study at any time without facing any consequences. The ethical procedures fostered adherence to accepted procedures for research with human subjects and contributed to the credibility and integrity of the study.

Results and Discussion

Preliminary Analysis

Measurement Model Assessment

Cronbach's alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE) were used to test the internal consistency reliability and convergent validity of the measurement model. The values of Cronbach's alpha > 0.70 and Composite Reliability > 0.50 were used to determine the reliability of the constructs and the validity of the constructs. As shown in Table 3, internal consistency reliability was satisfactory for all constructs. The Cronbach's alpha for Human–AI Collaboration was 0.89, and the Composite Reliability was 0.91, both of which reflected good reliability. Similarly, Job Satisfaction had the highest reliability for all constructs, Cronbach's Alpha = 0.91 and Composite Reliability = 0.93. The reliability of AI SE and Innovation BE was also good (Cronbach's alpha = 0.87, 0.88 respectively and Composite Reliability = 0.89, 0.90 respectively).

Average Variance Extracted (AVE) was used to test the convergent validity of the constructs. The quality of AVE scores was in the range 0.59 to 0.65, which is above the recommended score of 0.50. In particular, Human–AI Collaboration had an AVE of 0.62, Job Satisfaction 0.65, AI Self-Efficacy 0.59, and Innovation Behavior 0.61. The findings show that the variance explained by these constructs was above 50% in each of the constructs' measurement indicators, which is considered satisfactory convergent validity. The general psychometric properties of the measurement model were quite good, meaning that all of the components had good reliability and convergent validity for later analysis of the structural model.

Table 3: Reliability and Convergent Validity

Construct	Items	Cronbach's α	Composite Reliability	AVE
Human–AI Collaboration	8	0.89	0.91	0.62
Job Satisfaction	9	0.91	0.93	0.65
AI Self-Efficacy	6	0.87	0.89	0.59
Innovation Behavior	7	0.88	0.90	0.61

Confirmatory Factor Analysis (CFA)

To assess the measurement model fit and to ascertain the appropriateness of the observed indicators representing the latent constructs, Confirmatory Factor Analysis (CFA) was used. The measurement model proposed included four latent constructs: Human–AI Collaboration, Job Satisfaction, AI Self-Efficacy, and Innovation Behavior. The reliability and convergent validity of the measurement scales were first examined in CFA and then the structural relationship among the constructs was tested. As can be seen from the results of the present investigations displayed in Table 4, the reliability of all constructs was found to be satisfactory with internal consistency. Cronbach's alpha values were 0.87 to 0.91, which is greater than the recommended value of 0.70. Likewise, the CR values ranged from 0.89 to 0.93, which are high values, confirming the good reliability of the constructs and the consistency of the items measuring the latent variables. Average Variance Extracted (AVE) was used to measure convergent validity. This means the AVE scores were between 0.59 and 0.65, which is above the minimum AVE value recommended for 0.50. Specifically, Human–AI Collaboration (AVE = 0.62), Job Satisfaction (AVE = 0.65), AI Self-Efficacy (AVE = 0.59), and Innovation Behavior (AVE = 0.61) all had an AVE greater than 0.5. The findings show that all constructs accounted for over half of the variance in their corresponding indicators, providing good convergent validity. In summary, the results of the CFA analysis indicate that the measurement model has good psychometric properties. The constructs showed a high reliability and convergent validity which enabled using these latent variables for further analysis of the structural model.

Table 4: Confirmatory Factor Analysis (Reliability and Convergent Validity)

Construct	Items	Cronbach's α	Composite (CR)	Reliability	AVE	Assessment
Human–AI Collaboration	8	0.89	0.91		0.62	Accepted
Job Satisfaction	9	0.91	0.93		0.65	Accepted
AI Self-Efficacy	6	0.87	0.89		0.59	Accepted
Innovation Behavior	7	0.88	0.90		0.61	Accepted

Structural Model and Hypotheses Testing

Overall, Structural Equation Modeling (SEM) was used to analyze the hypothesized direct, mediating, and moderating relationships between Human–AI Collaboration, Job Satisfaction, AI Self-Efficacy, and Innovation Behavior. The structural model showed a satisfactory model fit, suggesting that the theoretical framework proposed was able to explain the relationships between the study constructs. The overall fit of the structural model was acceptable as the model fit indices met the recommended values ($\chi^2/df = 2.18$, CFI = 0.94, TLI = 0.93, RMSEA = 0.051). The results of direct path analysis showed that the Human–AI Collaboration positively and statistically significantly influenced Job Satisfaction ($\beta = 0.48$, $p < 0.001$) and thus confirmed H1. These results indicate that the use of collaborative interactions between employees and AI technology positively impacts the employee's work experience by improving the quality of decision making, reducing the routine workload, and making tasks more efficient. This finding aligns with recent research showing that Human–AI collaboration is an important organizational asset that enhances employee attitudes and well-being in the workplace.

In addition, Human–AI Collaboration had a crucial positive effect on Innovation Behavior ($\beta = 0.31$, $p < 0.001$), which lent support to this study's H2 hypothesis. Individuals who could successfully interact with AI systems were more likely to come up with innovative ideas, encourage others to promote these ideas, and put them into practice in their workplaces. Similarly, Job Satisfaction was found to have a significant relationship with Innovation Behavior ($\beta = 0.42$, $p < 0.001$), thus supporting H3. The result suggests that happy workers have higher motivation, innovativeness, and commitment to adopting new work practices, which ultimately leads to the innovation and competitiveness of the firm.

Additionally, the mediation analysis found that Job Satisfaction had a significant mediating effect between the variables of Human–AI Collaboration and Innovation Behavior. The indirect effect was statistically significant and the 95% CI did not cross zero with bootstrapping procedures which involved 5000 resamples and bias-corrected intervals, thus supporting H4. The results suggest that Human–AI Collaboration directly has a positive effect on employees' innovative behavior, and indirectly on innovative behavior via increased Job Satisfaction, resulting in partial mediation. This result underlines the importance of the value AI-enabled workplaces generates beyond operational efficiency, by enabling positive psychological experiences and thereby stimulating employee creativity. In addition, the moderating effect of AI Self-Efficacy is also statistically significant ($\beta = 0.19$, $p < 0.01$), which supports H5. The positive relationships between Human–AI Collaboration and Job Satisfaction were higher among employees who had higher self-efficacy of using AI technologies, as compared to employees that had lower AI self-efficacy. This discovery confirms that AI Self-Efficacy boosts employees' capacity to harness work tools with AI in a way that leads to positive work outcomes and increased satisfaction. The overall results of the structural model findings support the conceptual model proposed herein quite well. The findings indicate the Human–AI Collaboration plays a strategic role as a resource for the organization, which in turn directly increases Job Satisfaction and Innovation Behavior, and Job Satisfaction partially explains the relationship between collaborative AI and innovative work behavior. Furthermore, Human–AI Collaboration benefits are more pronounced for employees with higher AI Self-Efficacy, highlighting the need for fostering employees' AI-related skills. The results align with the Job Demands – Resources (JD – R) Theory, which suggests that motivational mechanisms through organizational resources help to create positive employee attitudes and behaviors. On a more practical note, the findings imply that banking institutions should not only be investing in AI technologies, but also in employee training and the development of AI skills to ensure optimal innovation results and competitive advantage in AI driven workplaces.

Discussion of Findings

The measurement model results confirm high levels of reliability and validity for the constructs used in the study to examine the Human–AI Collaboration, Job Satisfaction, AI Self-Efficacy, and Innovation Behavior in the banking industry. The Cronbach's alpha and Composite Reliability were greater than the recommended thresholds for all four constructs, which shows they had high internal consistency of measurement items. This implies that respondents responded to the questionnaire items in a uniform manner and therefore the reliability and stability of the measurement scales can be assured. In addition, the satisfactory AVE values indicate that the indicators suitably reflect the latent constructs. The AVE for Job Satisfaction is rather high (AVE = 0.65), indicating that the selected items are an appropriate representation of employees' satisfaction with their work environment, with AVE values for Human–AI Collaboration (AVE = 0.62), Innovation Behavior (AVE = 0.61), and AI Self-Efficacy (AVE = 0.59) also showing acceptable convergent validity. The results show that the measurement instruments are capable of measuring the theories used in the proposed research framework. The high reliability and validity of the Human–AI Collaboration construct suggests that employees perceived AI as a collaborative workplace tool more often than as an automation tool. Likewise, the high score on the AI Self-Efficacy measure indicated that workers could accurately assess their confidence in using AI technologies. The internal consistency of the Innovation Behavior scale also suggests that the behaviors employees reported were consistent across all of the three categories of idea generation, promotion and implementation. In conclusion, the results of the measurement model indicate that these measurement tools have been met and support the required conditions for PLS-SEM analysis. Based on this, the latent constructs can be assuredly introduced in the structural model to investigate the hypothesized relationships between Human-AI Collaboration, Job Satisfaction, AI Self-Efficacy and Innovation Behavior. The satisfactory measurement properties also enhance the credibility and robustness of the subsequent hypothesis testing and the evaluation of the structural model.

The results of the CFA suggest good construct validity and reliability for the proposed measurement model. Cronbach's alpha and Composite Reliability values were high indicating that the measurement items are consistently measuring the theoretical constructs. Moreover, the values of AVE higher than recommended suggest that the latent constructs fully account for the variance of the corresponding indicators. The measurement properties of the constructs were relatively high, with Job Satisfaction having the highest Composite Reliability score (0.93) and AVE score (0.65) which means that the indicators of Job Satisfaction provide the most reliable representation of the construct. Similarly, with regard to reliability and convergent validity, Human–AI Collaboration, AI Self-Efficacy, and Innovation Behavior all showed acceptable reliability and convergent validity, which will support the use of these constructs in the structural model. The results of the CFA therefore support the use of the proposed measurement framework in this study and suggest that the constructs are suitable to test the hypothesized relationships among Human–AI Collaboration, Job Satisfaction, AI Self-Efficacy and Innovation Behavior.

Policy Implications and Recommendations

This study's results offer significant policy insights for banking institutions, policy makers, tech developers and human resource managers aiming to harness the optimal value of Artificial Intelligence (AI) whilst fostering employee wellbeing and organization innovation. Overall, the findings suggest that Human–AI Collaboration positively influences Job Satisfaction and Innovation Behavior, and that AI Self-Efficacy has a positive impact on these relationships. Based on these results, the following arguments were made that organizational AI strategies should go beyond technologization and investment and embrace employee development, supportive leadership and good governance structures. First, banking regulators and policymakers need to create comprehensive national AI governance frameworks that foster responsible use of AI technologies and safeguard the rights of its employees while simultaneously encouraging ethical use of AI. To ensure that AI systems enhance human expertise, regulatory guidelines should set standards for transparency, accountability, data privacy, algorithmic fairness, and explainable AI. These policies would boost trust in AI-driven systems, and ease the path towards their successful adoption in financial institutions. Second, bank management should focus on human-centric AI implementation by developing AI systems that assist human personnel in decision-making, customer service, and daily operations, instead of taking over their functions. Human–AI Collaboration must be integrated into organizational structures and processes to enhance productivity while maintaining autonomy and professional discretion of employees. AI should be used as a smart decision-maker that helps the employees to do their job better and encourages them to undertake more analytical and strategic tasks. Third, organizations must invest heavily in building employee AI Self-Efficacy through ongoing learning and professional development, digital literacy training, and real-world AI learning experiences. To ensure that employees benefit from AI literacy, data interpretation, ethical use of AI and practical experience with AI applications, structured training programs should focus on those areas that will result in higher gains for employees with higher AI Self-Efficacy. Regular learning will help employees gain confidence in the use of AI technologies and contribute to the smooth integration of digital transformation in the organization.

Fourth, Job Satisfaction should be made the central focus of HR policies for enhancing organizational innovation. HR teams must create a supportive work culture that fosters employee engagement in AI adoption, acknowledges creativity, and offers development chances. Incorporating employees into decision-making about AI can help minimize resistance to technological shifts and boost commitment and psychological connection with digital transformation efforts. In addition, banks need to promote a culture of ongoing innovation by promoting collaboration between individuals with technology expertise and business-focused skills. The use of AI-powered knowledge sharing tools, team-based problem-solving projects, and incentivizing innovation can encourage employees to think outside the box and come up with creative solutions. These efforts reinforce the correlation of HACC and Innovation Behavior and improve the adaptability of organizations in the financial markets of today.

Lastly, balanced policies and practices in the future should combine technological development with the welfare of employees. There is a need for investment decisions that look at infrastructure, training people, ethics and organizational culture. By integrating cutting-edge technological features with skillful human capital development, financial institutions can secure sustainable competitive advantage, enhance service quality, and foster long-term organizational innovation through a comprehensive AI strategy. These recommendations offer a practical blueprint for policy makers and banking leaders to help them create resilient, innovative, and human-centric organizations powered by AI.

Conclusion

This research explored the effect of Human–AI Collaboration on Innovation Behavior and the mediating effect of Job Satisfaction, and the moderating effect of AI Self-Efficacy in the banking industry. The study was grounded on the Job Demands–Resources (JD–R) theory and proposed that Human–AI Collaboration is a strategic organizational resource which enhances the work experience and boosts the innovation of the employees. The results confirm the proposed conceptual model as they show the positive relationship between Human–AI Collaboration and both Job Satisfaction and Innovation Behavior. In addition, the results show that Human–AI Collaboration is partly mediated by Job Satisfaction, suggesting that people who are more satisfied with working in a context where they can collaborate with AI are more inclined to adopt creative approaches in problem-solving and innovative working methods. The results also indicate that AI Self-Efficacy positively influences the association between Human–AI Collaboration and Job Satisfaction, underscoring the importance of mistrust in AI technologies among the employees. The study has some theoretical and practical contributions. To the extent that feasible, it extends the application of the JD–R Theory and integrates the results of the Human–AI Collaboration, Job Satisfaction, AI Self-Efficacy and Innovation Behavior into a comprehensive model that could explain how the use of AI-supported organizational resources affects the outcomes of work. It also highlights the synergies between technological resources and individual skills, in line with the existing literature on the application of AI in HRM and OBE. The findings highlight the need for organizations to adopt a human-first strategy in their AI implementation, invest in their employees' skills and knowledge, and create an environment that fosters innovation and employee satisfaction. Technological innovation along with employee development will help the banking industry reach sustainable performance in their institutions, and give them the competitive advantage in the financial services industry increasingly becoming digital.

Limitations

This study has a number of limitations, however, that should be noted. The first one was the cross-sectional research design which limits the possibility of drawing causal relationships between Human–AI Collaboration, Job Satisfaction, AI Self-Efficacy and Innovation Behavior. Longitudinal studies will provide more conclusive evidence of the dynamic effect of adopting AI over time. Second, the study focused on banking, which may limit the generalizability of its findings to other sectors of the economy, such as healthcare, manufacturing, education, public administration, and so on. The dynamics of the relationships observed can change because contexts of organizations may have different levels of AI adoption, maturity, and work responsibilities. Third, although the scales were fixed, the study relied upon self-reported survey data and this may introduce common method bias and social desirability bias. In future research, using supervisors' evaluation and objective organizational performance indicators would help to enhance the findings' validity. Fourth, this study examined only some of the variables with the JD–R model. Other organizational and individual factors such as organizational culture, leadership style, psychological safety, trust in AI, technology readiness, and perceived organizational support might also affect the reactions from employees to AI in the workplace. Lastly, the research took place in a particular national context, and employees' understanding of how to use AI for collaboration and innovation could be affected by cultural differences. Thus, care should be taken in generalizing across countries or institutional settings.

Future Research Directions

Based on this study, the researchers suggest that future research would benefit from employing the Longitudinal and Experimental research design to examine the evolution of Human–AI Collaboration over time and the learning and adjustment of employees to the growing use of AI in the workplace. This would give a more robust insight into cause and effect and the impact of AI use on employee attitude and innovation in the long-term. To evaluate the proposed framework's external validity and to understand the impact of culture, institutional, and technological variations on Human–AI Collaboration, researchers need to consider it in different industries and countries.

The theoretical model could be extended to include other mediators, like employee engagement, knowledge sharing, psychological empowerment, organizational commitment, trust in AI, employee resilience, and psychological safety, in future studies. Similarly, moderators such as ethical leadership, digital organizational culture, AI transparency, technology readiness, learning orientation, and organizational support may help gain deeper insights into the context in which Human–AI Collaboration yields positive results. Comparative studies of different AI technologies, such as generative AI, predictive analytics and intelligent automation, would also aid the understanding of the impact these technologies have on employee behavior. Furthermore, the potential of developing other theories of value creation from AI technologies, such as Social Exchange Theory, Dynamic Capability Theory, Technology–Organization–Environment (TOE) Framework, or the Ability–Motivation–Opportunity (AMO) Theory to better explain the mechanisms of value creation in organizations is an area that needs further investigation. Finally, combining qualitative interviews or case studies with quantitative survey results might provide deeper insights into employee experiences, challenges faced by organizations, and successful practices for implementing human-centered AI strategies. This type of study could help in creating more holistic AI management approaches that can aid the sustainable innovation of organizations and the transformation of their workforces.

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