

Exploring AI-employee collaboration from a Cognitive Appraisal Perspective

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Abstract

Within the rapidly evolving digital workplace landscape, the collaboration between artificial intelligence (AI) and employees is a subject of increasing research focus for its impact on both business and employee outcomes. Despite this, research on the implications for employees remains limited. To address this gap, we develop a theoretical model grounded in cognitive appraisal theory, investigating the implications of AI-employee collaborations for employee thriving at work and the associated boundary conditions. Analysing data from 214 UK-based employees, we find a positive association between AI-employee collaboration and employee thriving, mediated by employee challenge appraisal. Further, employee connectivity is found to moderate the relationship between challenge appraisal and thriving, strengthening it in higher connectivity scenarios. This study offers a novel perspective on the role of cognitive mechanisms and workplace interactions, contributing theoretical insights. For HRM practitioners, the findings provide guidance on tailoring strategies to effectively integrate AI into the workplace.

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1.Introduction

Employee thriving, defined as a combined sense of learning and vitality (Spreitzer et al., 2005), is a positive psychological state linked to desirable employee outcomes such as job satisfaction (Marchiondo, Cortina, & Kabat-Farr, 2018) and enhanced performance (Gerbas et al., 2015). Research has since explored factors that could promote employee thriving, highlighting the importance of the work context (Kleine et al., 2019). However, recent shifts in how traditional HRM functions, such as hiring, task allocation, and employee management, are carried out—the rise of algorithmic HRM—has substantially disrupted the work context. Algorithmic HRM relies on digital data and algorithms to optimize processes and automate HRM decisions (Duggan et al., 2023; Meijerink et al., 2021, 2023), introducing new forms of organizational workflows, and raising concerns about algorithmic surveillance (Newlands, 2020), people analytics (Gal et al., 2020) and algorithmic control (Veen et al., 2020). In this evolving landscape, employees are increasingly encountering unfamiliar experiences, particularly in the form of AI-employee collaboration, as organizations adapt to these digital transformations (Budhwar et al., 2022; Malik et al., 2023a & 2023b). According to the HRM literature, AI is defined as the “ability of a manmade system comprising of algorithms and software programs, to identify, interpret, generate insights, and learn from the data sources to achieve specific predetermined goals and tasks” (Chowdhury et al., 2023). In this vein, our study focuses on AI software tools (e.g., business intelligence), which dominate HRM applications due to their versatility and cost-effectiveness, rather than humanoids or hardware robots, which are less prevalent and often limited to specific contexts (Cameron et al., 2024; IBM Consulting, 2023).

AI-employee collaboration refers to the integration of AI technologies into the HRM processes and decision-making activities of employees, fostering a symbiotic partnership between human intelligence and machine intelligence algorithmic capabilities (Kong et al.,

2023; Chowdhury et al., 2022). It is a crucial component of algorithmic HRM by embedding machine learning, deep learning, natural language processing and vision processing algorithms that both automate and augment human decision-making and mastery (Meijerink et al., 2023; Chowdhury et al., 2022). So far, research has shown contradictions in terms of what this new trend of AI-employee collaboration means. On one hand, various studies have highlighted the disruptions, unfamiliar changes and obstacles that employees need to overcome when working with AI (Brown et al., 2024). These include skill mismatches, loss of control, and stress induced by algorithmic surveillance (Zhou et al., 2023; Malik et al., 2023a; Budhwar et al., 2022). On the other hand, emerging research has started to suggest that it is not necessary a bad thing (Jarrahi et al., 2023). For instance, Kong et al. (2023) showed that the dynamic interaction between employees and AI serves as a proactive approach to enhance employees' career orientation longevity and satisfaction while Chen et al. (2023) showed that AI-employee collaboration positively influences employees' learning orientations and behaviours. Similarly, Chowdhury et al. (2022) showed that AI-employee collaboration generates value for businesses.

In this dynamic context, employee connectivity—defined as the degree to which employees feel meaningfully linked to their colleagues, work environment, and organizational systems—plays a pivotal role in mitigating challenges and amplifying positive outcomes (Dutton & Heaphy, 2003; Hargadon, 2006). Employee connectivity fosters social capital and knowledge-sharing, enabling individuals to adapt to and embrace AI-driven transformations (Parker & Grote, 2022). By enhancing interpersonal relationships and providing support systems, connectivity can buffer the challenges associated through peer learning, observations and sharing (Brown & Duguid, 1991). It can also enable the co-creation of value, as employees feel more integrated and better equipped to thrive amidst

technological disruptions (Carmeli & Spreitzer, 2009). However, empirical evidence on the role of employee connectivity in the context of AI-human collaboration remains scarce.

Given the multifaceted complexities embedded in this new trend of AI-employee collaboration, thriving becomes particularly pivotal as employees need both vitality and learning to manage such complexities in the workplace. Unfortunately, studies examining AI-employee collaboration and employee thriving, including the mechanism that underly this phenomenon, remain limited. Despite the growing interest and significant advancements in understanding the integration of AI within workplaces (Vrontis et al., 2023), a comprehensive understanding of how this integration translates into tangible benefits for employees remains elusive (Chowdhury et al., 2024). The literature gap has since shifted from identifying factors that drive/inhibit AI-employee integration to develop collaborative intelligence capability within the organisations for understanding the impact of such collaborative intelligence capabilities on employee thriving, as also highlighted in this special issue call (Malik et al., 2024) and research (Le et al., 2024; Budhwar et al., 2023). Additionally, knowledge of the specific mechanisms underlying AI-employee collaboration and thriving can inform organizational implementations of AI technologies conducive to generating positive employee outcomes. This leads us to the following research questions motivating our current study, representing a critical and timely inquiry in the field of algorithmic HRM and thriving workforce.

RQ: What is the implication of AI-employee collaboration for employee thriving within the workplace?

We use Cognitive Appraisal Theory (CAT) (Lazarus & Folkman, 1984 & 1987) as the theoretical basis to focus on the cognitive mechanism employees exhibit when facing specific challenges stemming from AI-human collaboration. Our focus is on exploring how the assessment of challenges (i.e., challenge appraisal), particularly those arising from AI-

employee collaboration, is associated with employee thriving and examining how employee connectivity affects this relationship. While existing research has highlighted the significance of organizational factors in the successful adoption of AI technologies (Parker & Grote, 2022; Seeber et al., 2020), the specific cognitive pathways through which AI-employee collaboration associates with employee-related outcomes remain underexplored. Therefore, our study bridges this gap by understanding how cognitive challenge appraisal of AI-employee collaboration contribute to enhancing or impeding employee thriving within the organizational context. By doing so, this study sheds light on the complex cognitive process that employees undergo when interacting with AI technologies. By examining the moderating influence of employee connectivity, our study examines the conditions that can influence the association between AI-employee collaboration and employee thriving, thus enabling a more nuanced understanding, which is sparse in the existing HRM research in AI.

2.Theoretical background and Hypothesis development

2.1 Cognitive-appraisal theory

CAT goes beyond prior work that takes a priori approach to categorize employee experiences into different stressors suggesting that an individual's perception and evaluation of an event or situation matter for their subsequent emotional and behavioural responses (Lazarus & Folkman, 1984). The limitation of a priori categorization is that in reality an experience can be perceived in different ways (Cavanaugh et al., 2000). Indeed “many everyday stressors are neither clearly positive nor negative and so are most likely to be open to personal appraisal” (Hobfoll, 1989, p. 519).

The key tenet of CAT is the appraisal processes: the assessment of a potential threat or benefit (primary appraisal) and the evaluation of the resources available to cope with this threat or exploit the opportunity (secondary appraisal). The outcome of the appraisal process determines whether an individual experiences stress, motivation, or other emotional states,

which in turn influences their behavior and coping strategies (Lazarus & Folkman, 1984 and 1987). Therefore, based on CAT, stressors (i.e. environmental conditions) are not the direct antecedent of reaction. Rather it is the cognitive appraisal of the stressors as challenging or hindering that guides the subsequent responses (Rosen et al., 2020; Majeed & Naseer, 2021; Biggs et al., 2017; Webster, Beehr & Love, 2011). Stressors that are perceived as offering the opportunities for growth and the potentials for rewards belong to challenge appraisals and those perceived as hindering one's goal pursuit and threatening wellbeing belong to hindrance appraisal (Lazarus & Folkman, 1984).

CAT provides an appropriate theoretical framework to interpret how employees perceive the integration of AI into their work processes because it is difficult to categorize AI-employee collaboration to either a challenge stressor or a hindrance stressor category. AI-employee collaboration involves using AI analytics for strategic decisions, chatbots for routine inquiries, and machine learning to support medical diagnoses, providing preliminary assessments for doctors to review (Raisch & Fomina, 2023). These are novel experiences that are marked by a high degree of uncertainty, complexity, and ambiguity (Sowa et al., 2021). Therefore, CAT helps to understand and unearth the underlying cognitive processes and the conditions that facilitate employee thriving. The theoretical model of our research is presented in figure 1.

Insert Figure 1: Theoretical Model.

2.2 AI-employee collaboration and challenge appraisal

Drawing from CAT, we first propose that AI-employee collaboration will be positively associated with employee challenge appraisal due to the automation and augmentation capabilities of AI, which provide opportunities for growth and mastery. AI-

employee collaboration is about employees and AI systems working together (Sowa et al., 2021). The unique features of AI can offer employees significant learning and development opportunities. For example, AI tools are capable of automating routine, time-consuming tasks, freeing employees from managing large volumes of data or repetitive processes (Raisch & Fomina, 2023; Verma & Singh, 2022). This automation allows employees to conserve their cognitive and emotional energy, enabling them to focus on higher-level tasks such as creative problem-solving, thereby boosting their confidence in task mastery (Hu et al., 2023) and fostering a positive appraisal of challenges. Moreover, prior research has indicated that employees can gain new insights, predictive analytics, and pattern recognition through AI collaboration—outcomes that may not be easily accessible through human cognition alone (Amabile, 2019). This, in turn, leads employees to perceive AI collaboration as an opportunity to harness AI's strengths in tandem with their own for personal growth and development.

The augmentation capabilities of AI (Jia et al., 2023) also means that when working with AI, employees will obtain support in data analysis and decision-making (Jarrahi, 2018). For instance, research has suggested that, by leveraging AI's analytical and computational capabilities, employees are more likely to feel competent and confident in their roles (Chowdhury et al., 2022). Another study found that using AI-powered smart bots within an online game significantly improved the performance of the human team (Shirado & Christakis, 2017). Therefore, AI systems with its superior ability to process information rapidly and to perform complex analytical tasks can be perceived positively by employees as enhancing their own cognitive capabilities, especially in dissecting and understanding intricate issues, leading to a challenge appraisal focusing on growth and mastery.

Another possibility that working with AI can be perceived by employees as providing potentials for growth is the continuous learning environment induced by AI-employee

collaboration. Research shows that AI systems can offer personalised learning experiences and real-time feedback, enhancing employees' ability to adapt to new challenges and continuously develop their skills (Malik et al., 2022). Knowing that they have the tools to learn and adapt can positively influence their challenge appraisal. For example, access to AI tools and resources for learning and adaptation empowers employees by providing them with the means to tackle challenging tasks efficiently. This empowerment fosters a sense of autonomy and control, which are necessary for viewing challenges not as obstacles but as opportunities for growth and improvement.

Hence, from the lens of CAT, collaborating with AI can be perceived as enabling one's opportunities to learn and adapt. This perception means challenges are no longer seen purely in terms of their potential stress or threat but are evaluated in terms of the opportunities they present for utilizing AI to achieve success. Therefore, we propose the following:

H1: AI-employee collaboration will be positively associated with employee challenge appraisal.

2.3 Challenge appraisal and employee thriving

Challenge appraisal in the workplace context involves the individual's assessment of the environmental condition and their perceived ability to navigate it successfully. This perception is crucial because, based on CAT, it influences how employees react emotionally, cognitively, and behaviourally (Lazarus & Folkman, 1984). According to CAT, challenge appraisal indicates that the condition is goal facilitating which means employees are more likely to proactively respond to situational stimuli with an approach-oriented coping strategy (Searle & Auton, 2015). Such proactive and approach orientation is an important manifestation of vitality and learning (c.f. Matzler & Mueller, 2011).

In addition, based on CAT, challenge appraisal encompasses positive emotions such as enthusiasm, confidence, and a sense of purpose (Sharma and Gupta, 2023), which are important for the vitality component of thriving. These positive emotions are also conducive to fostering a growth mindset (Elkheloufi & Yean, 2022), where obstacles are not avoided but embraced as essential en-route to task mastery and personal development. Altogether, considering these arguments, we develop the following hypothesis.

H2: Employee challenge appraisal will be positively associated with employee thriving.

2.4 The mediating role of challenge appraisal

Integrating the above reasoning and following CAT, we further hypothesize the association between AI-employee collaboration and employee thriving is mediated via challenge appraisal. CAT suggests the subjective nature of stress and coping, emphasizing that the individual's appraisal of the situation determines their emotional and behavioural responses, i.e., the process through which employees interpret and assign meaning to the situation (Park & Folkman, 1997). The transformation of AI-employee collaboration related challenges from potential stressors to catalysts for thriving depends on individual beliefs and perceptions. This process is deeply rooted in the cognitive appraisal of the situation, where the individual's beliefs about their capabilities, the inherent value of the challenges presented by AI, and their expectations of the outcomes can significantly influence their response to these challenges.

Specifically, AI-employee collaboration introduces new dynamics into the workplace, potentially altering the nature of tasks, the workflow, and the skills required to perform effectively (Au-Yong-Oliveira et al., 2019; Wilson et al., 2017). Such changes, although disruptive, can be perceived as enabling opportunities for growth, learning, and enhanced productivity. This is because the automation and augmentation embedded in AI-employee

collaboration have the potential to elevate the importance of critical thinking and creative intelligence in the workplace (Daugherty et al., 2019) and equip employees with new tasks in new roles (Park et al., 2020; Shin, 2022), potentially leading to a positive evaluation of these changes and eliciting favourable responses. So it is not just a matter of technological adoption but a catalyst for a broader transformation in personal growth that could be oriented. So when employees assess these changes and their implications, they are likely to perceive them as a challenge appraisal, which in turn associated with their thriving at work.

Research indicates that viewing challenges as opportunities for growth and learning can promote an approach and growth orientation towards future pursuits of innovation and building resilience (Liu et al., 2020; 2021). In this context, these positive influences motivate employees to seek new discoveries, identify new possibilities, and being open to failure so as to achieve learning. Moreover, by perceiving challenges as opportunities for growth, employees build an array of approach-oriented coping strategies and problem-solving skills. This process not only equips them to handle current challenges more effectively but also prepares them to navigate future uncertainties with greater confidence, thus enhancing their ability to adapt (Carnevale & Smith, 2013) and ultimately vitality and grow. Therefore we hypothesize the following:

H3: The relationship between AI-employee collaboration and employee thriving will be positively mediated by employee challenge appraisal.

2.5 The moderating role of employee connectivity

CAT highlights the importance of secondary appraisal in evaluating the resources available to employees to cope with AI-related challenges (Steptoe & Vogele, 1986; Lazarus & Folkman, 1984 and 1987). According to CAT, the appraisal process is not merely a passive assessment but a dynamic interaction between the individual and their environment, shaping

their emotional and behavioural responses to situations encountered in the workplace (Folkman et al., 1986). When employees face a situational stimulus, their appraisal involves evaluating whether a given challenge poses a threat or presents an opportunity for growth alongside an evaluation of resources and options available for coping. In this context, the stock of resources plays a moderating role in affecting the magnitude of the evaluation. We focus on employee connectivity given its potential to influence the stock of resources.

Employee connectivity describes the extent to which employees feel connected with their colleagues and the broader organizational network (Liu et al., 2021). It provides a mechanism for employees to have shared understanding, mutual support, and collective resilience, making the workplace conducive to the exchange of ideas, emotional support, and collaborative problem-solving (Spreitzer et al., 2012). Therefore, at a higher level of employee connectivity, employees have access to more social resources and support (such as emotional support, practical assistance, and valuable information), which fosters a sense of belonging and collective efficacy (Kahn, 1990). This positive sense can make employees more likely, than those with a lower level of connectivity, to view a challenge appraisal as manageable and meaningful, which ultimately promotes thriving.

A higher level of employee connectivity also suggests a higher quality of interpersonal relationships (Dutton & Heaphy, 2003), the more extent of collaborative networks, and the higher strength of communal ties within an organization (Hargadon, 2006). These elements are crucial for fostering an atmosphere where employees not only feel capable of tackling challenges but also see the value in doing so as part of a cohesive and supportive community (Macey and Schneider, 2008). Therefore, when employees feel a stronger (vs. lower) sense of connection to their colleagues and the organization, they are more embedded in a supportive social fabric and likely to learn (Brown & Duguid, 1991), that can enhance the positive effects of viewing challenges as opportunities for personal and

professional growth, which ultimately fosters thriving (Spreitzer et al., 2005). Building on the above arguments, employee connectivity not only enhances the resources available for coping with challenges but also influences how employees perceive and respond to these challenges. This highlights the intricate interplay between individual cognition (challenge appraisal) and the social context (employee connectivity and support within the organization) in shaping important workplace outcomes like thriving. Therefore, we hypothesize the following.

H4: The relationship between employee challenge appraisal and employee thriving is positively moderated by employee connectivity such that when employee connectivity is higher (vs. lower), the strength of the direct relationship is higher (vs lower).

3.Methodology

3.1 Sample and procedure

Our research design employed a survey-based methodology to gather empirical evidence for testing the proposed model (Figure 1), collecting data from UK-based employees. The UK is an ideal context for our study due to its leadership in AI innovation and wide adoption across sectors, supported by a National AI strategy and substantial government investment in research and development. The UK government has proactively developed policies, including the 2018 AI Sector Deal, a £1 billion initiative, to enhance the UK's global AI leadership (UK National AI Strategy, 2021). By 2022, AI technologies contributed £3.7 billion to the economy, with 17% of businesses adopting AI (UK DSIT Report, 2023). The UK ranks third globally in the 2021 AI Readiness Index and leads in Western Europe (Hooson, 2024).

We used the following criteria to select participants for the study: (1) they must be UK-based and hold full-time positions, ensuring a consistent geographical and economic

context; (2) they must work in organizations that actively use AI tools, ensuring insights come from those directly working with AI; (3) they are required to use AI tools regularly at work, to provide firsthand experience with AI-employee collaboration; and (4) individuals who recently participated in similar studies were excluded to avoid response bias.

AI is a broad field encompassing various tools, technologies, and methodologies, each with different implications depending on the user's knowledge, expertise, and the tasks they aim to accomplish. The definition of AI often varies depending on individual perspectives. Therefore, we presented the definition of AI used in this research (from Chowdhury et al., 2023), at the start of the survey. Additionally, respondents were asked specifically about the AI applications they are required to use in their workplace as part of their job roles. This ensured that responses were not limited by individual interpretations of AI, but rather focused on practical and contextualized examples of AI integration in their professional activities.

The survey was distributed via the Prolific platform, a widely recognized tool for recruiting diverse and reliable participants for research studies. Before launching the full-scale study, we conducted a pilot study with a sample of ten employees to test the initial version of the questionnaire. The results of the pilot study confirmed that the screening criteria effectively identified suitable participants, and the attention checks successfully ensured the reliability and attentiveness of the respondents. Additionally, no issues were reported by participants regarding the clarity of the statements or their ability to complete the survey. The final sample used for analysis comprised of 214 participants out of 280, who registered for the survey (see Table 1). All the 214 participants provided examples of AI applications that they were using at the workplace, which ranged from business intelligence and simulation software, generative AI tools subscribed by the organization, people analytics platforms, and customer relationship management tools. Respondent characteristics are presented in table 2. We employed the G*Power tool to evaluate the adequacy of our sample

size by conducting an F-test for a linear multiple regression fixed model with an R² deviation to zero (Bartlett, 2019). The analysis yielded a required sample size of 107 to achieve a medium effect size of 0.15, with an alpha level set at 0.05 and a power of 0.95, considering two predictor variables in our model. This result demonstrates that our sample size of 214 is more than adequate to test the conceptual model.

Insert Table 1: Response checks and total sample

Insert Table 2: Sample characteristics

3.2 Measures

The measurement items used in this study are derived from scales validated in the existing research (Appendix 1). AI-human collaboration is derived from Kong et al. (2023). A sample item was, “AI participates in my decision-making process”. The three challenge appraisal items were derived from LePine et al. (2016). A sample item was, “Working to fulfil the demands of collaborating with AI tools in my job helps to improve my personal growth and well-being”. The eleven items for employee thriving were derived from Carmeli & Spreitzer (2009). We chose to operationalize thriving at work as a combination of the two dimensions of learning and vitality together, as reported in the previous research (Han et al., 2024; Ren et al., 2022; Walumbwa et al., 2017; Wallace et al., 2016; Cullen et al., 2015). A sample item was, “At work, I find myself learning often”. Finally, seven items for employee connectivity were derived from Carmeli & Spreitzer (2009). A sample item was, “The relationships we have in my organisation enable me to learn new things”. We included age (coded as 1: 20-35 years; 2: 36-45 years; 3: 46-55 years; 4: above 55 years), gender (1: male; 2: female; 3: others), educational qualifications (1: bachelors/graduate; 2: Masters/post-graduate; 3: doctorate; 4: other diploma), and the sector (1: marketing/retail; 2: hospitality; 3: finance; 4: manufacturing; 5: information technology) in which the firm operates as control variables due

to their potential influence in influencing employee experience. Results of hypothesis testing with and without control variables were consistent. Therefore, we presented the findings without control variables for parsimony.

We used few reverse-scaled statements to detect consistency in responses. Additionally, we included an open-ended question that required participants to enter specific terms into a text box, as attention check. We monitored the response time, setting a minimum threshold of 10 minutes, determined to be an appropriate benchmark based on the pilot study.

3.3 Common method bias and multi-collinearity

Although cross-sectional studies are popular in the extant literature on AI related phenomenon (Chowdhury et al., 2022; Singh et al., 2022; AlNuaimi et al., 2022), data collected through self-reporting methods are often vulnerable to common method bias (CMB) (Podsakoff et al., 2003). Following guidelines from established research (Podsakoff et al., 2012), our procedural safeguards included offering explicit instructions, ensuring participant anonymity, limiting the survey length to reduce respondent fatigue, strategically arranging the statements to separate the independent and dependent variables spatially, and disguising the expected relationships between the variables.

In our statistical analysis, we determined the total variance each construct accounted for, exceeded 50%, which suggests that CMB is unlikely an issue in the data (Hair, Ringle, and Sarstedt, 2013). To further assess the presence of CMB, we conducted Harman's single factor test (Podsakoff et al., 2003). The findings showed a common method variance (CMV) of 0.425, which, is below the commonly accepted benchmark of 0.50 alleviating CMB concerns. Additionally, we applied the marker variable technique (Williams, Hartman & Cavazotte, 2010) to test for CMB. The marker variable selected was consumer green purchase intention from the green consumer behaviour literature (Chen & Chang, 2012), based on its theoretical non-relevance to the main study variables, and aligning with

recommendations in the literature for theoretical irrelevance (Simmering et al., 2014). The results revealed that variation inflation factors (VIFs) are less than 3.3 (table 3). The full collinearity VIF is also tested for multi-collinearity (Kock 2015). The obtained results (table 3) align with the recommended thresholds in the literature, being acceptable at ≤ 5 and ideally at ≤ 3.3 (Kock, 2015).

Insert Table 3: Common method bias and collinearity test

4. Results

To assess the measurement model, we examined the reliability of the items for each construct (as detailed in table 4) and found them over the recommended threshold of 0.70 (Hair et al., 2020). The Cronbach's alpha and composite reliability for each construct (also presented in table 4) was over the recommended minimum threshold of 0.70 (Hair et al., 2020). To evaluate the convergent validity of the constructs, we utilized the average variance extracted (AVE) and found that the values exceeded the 0.50 threshold (Hair et al., 2020). Our analysis (presented in table 4) revealed that the square root of the AVE was higher than the correlations between constructs, confirming adequate discriminant validity (Fornell & Larcker, 1981).

Insert Table 4: Descriptive and reliability statistics

The proposed model was evaluated using the SPSS PROCESS macro version 3.0 (Hayes, 2017). This tool allows for the concurrent estimation of both direct and indirect effects within a single mediator model and has been used in existing research on thriving (Han et al., 2024; Gartzia, 2023; Ren et al., 2022; Giroux et al., 2022) Moreover, the results produced by PROCESS and SEM analysis are largely identical as outlined in Hayes et al. (2017).

We tested Hypotheses 1, 2 and 3 concerning the relationship between human-AI collaboration, challenge appraisal and employee thriving using Model 4 in PROCESS (Hayes, 2017). Based on the results presented in Table 5, we found a positive and significant direct

association between AI-employee collaboration and challenge appraisal (co-eff = 0.39, $p < 0.001$, H1 accepted); positive and significant direct association between challenge appraisal and thriving (co-eff = 0.685, $p < 0.001$, H2 accepted). We found a positive indirect effect of challenge appraisal on the relationship between AI-employee collaboration and thriving (indirect effect = 0.267, 95% CI [0.013, 0.154], therefore confirming the mediation hypothesis (H3 accepted). The R-square value for challenge appraisal is 0.201, and thriving is 0.581.

Insert Table 5: Results of hypothesis testing

To assess the statistical significance and confidence intervals for moderated mediation effects, bootstrapping with 5,000 samples was employed by using SPSS Macro Model 14 (Hayes, 2017). The result presented in table 5 showed that the interaction term of employee connectivity (moderator) was positive and significant: (co-eff=.0836, se=.036, $p=.02$), which explained additional 1.1% of variance in thriving ($\Delta R^2 = 0.0110$, $F = 5.463$, $p = .02$). When connectivity is lower (1 SD below the mean), the relationship between challenge appraisal and thriving was smaller and positive (effect = .513, $p < 0.001$). In contrast, the relationship was positive and stronger (effect = .684, $p < .001$) for those with higher connectivity (1 SD above the mean), as shown in Figure 2. Additionally, the index of moderated mediation was also significant (index = .033, SE = 0.018, 95% CI = [0.002, .071]).

Insert Figure 2: Moderation Interaction Results

The analysis, as presented in table 6, reveals that the control variables—age, gender, educational qualifications, and the sector in which the firm operates—do not have a statistically significant impact on challenge appraisal or employee thriving. This finding suggests that these demographic factors do not meaningfully influence how employees perceive and appraise challenges and their overall thriving at work.

5. Discussion

The findings support *Hypothesis 1*, demonstrating that AI-employee collaboration is positively associated with challenge appraisal. This suggests that AI-employee collaboration encourages individuals to perceive working with AI in their workplace across various contexts as challenge appraisal rather than hindrance (or threat) (Koo et al., 2021; Kong et al., 2021), thereby fostering a growth, learning and adaptive mindset. This positive association can be attributed to the complementary capabilities AI tools offer (Raisch & Fomina, 2023). Specifically, AI tools can assist employees by automating routine tasks, enabling them to focus on complex, creative, and strategic responsibilities that enhance human employees' sense of purpose, mastery and career sustainability (Kong et al., 2023). Therefore, augmenting human capabilities with AI technologies (i.e., AI-employee collaboration) transforms the perception of challenges into opportunities for growth and innovation rather than sources of stress. This collaboration also equips employees with valuable workplace resources—such as real-time data insights and analytics for decision-making—which can enhance their confidence in effectively managing tasks (Tschang & Almirall, 2021; Raisch & Krakowski, 2021).

Our results support *Hypothesis 2* that challenge appraisal is positively associated with employee thriving. This result aligns with existing literature suggesting that how employees perceive and interpret work-related demands significantly influences their workplace thriving (Lazarus & Folkman, 1984). While Kong et al. (2023) demonstrated the positive impact of AI-employee collaboration on career sustainability, and Chowdhury et al. (2022) on business productivity, our study extends these insights by emphasizing the role of challenge appraisal (cognitive mechanism) in fostering employee thriving within AI-driven work environments. Challenge appraisal allows employees to engage proactively with their tasks, leveraging the perception of challenges as motivating rather than debilitating (LePine, 2022). This mindset

encourages adaptive behaviours, which not only enhance individual capabilities but also contribute to a broader sense of fulfilment and purpose at work (Keating & Heslin, 2015 Spreitzer et al., 2005).

The findings of this study confirm *Hypothesis 3*, demonstrating that challenge appraisal positively mediates the relationship between AI-employee collaboration and employee thriving. This mediating role shows the importance of challenge appraisal as a cognitive mechanism that transforms the functional benefits of AI-enabled collaboration into meaningful psychological and developmental outcomes for employees. In this context, the process of engaging with and overcoming challenges is inherently growth-oriented (Webster, Beehr & Love, 2011), which is characterized by the acquisition of new skills, expanding expertise, and a deeper understanding of their own capabilities and potential (Dimitrova, 2020; Prem et al., 2017). While existing research has studied the direct influence of AI-employee collaboration on employee productivity and career satisfaction (Kong et al., 2023), and the moderating role of AI-employee collaboration on job demands, self-efficacy, and learning orientation (Chen et al., 2023), our study advances the literature by shifting the focus to the cognitive appraisal process through which employees derive personal and professional growth from such collaborations.

Finally, the results confirm *Hypothesis 4* that employee connectivity positively moderates the relationship between challenge appraisal and employee thriving. Employee connectivity enhances the positive effects of challenge appraisal on thriving by fostering access to social support, collaborative problem-solving, and shared resources (Goh et al., 2022). This interconnectedness creates an environment where employees can leverage collective expertise and emotional support, transforming challenging situations into opportunities for growth and further reinforcing their sense of thriving (Carmeli & Spreitzer, 2009).

6. Implications

6.1 Theoretical Implications

The first originality of this research lies in providing theory-driven, empirically tested evidence that AI-employee collaboration will encourage employees to view challenges as opportunities for learning and growth. By providing support and augmenting employees' cognitive capabilities and higher order thinking skills, AI-employee collaboration can help reframe potentially challenging situations into ones that are perceived as manageable and beneficial (Boswell et al., 2004). In this direction, our findings contribute to resolve the seemingly contradictory arguments in the literature regarding the increased integration of AI in the workplace. Tensions abound about the disruptions of emerging technologies such as AI bring to the people management domain, including for instance increased concern over employment security, skill obsolescence, and decision-making autonomy (Chowdhury et al., 2024; Zhou et al., 2023; Budhwar et al., 2022). These tensions have created a polarizing discourse on benefits and risks of AI for the modern workforce. On the other hand, emerging research suggests that employees can develop career competencies and work skills through their interaction with AI, ultimately benefiting their career sustainability (Kong et al., 2023). We enrich this emerging line of research by showing that this new algorithmic HRM pattern of working with AI can actually contribute to a thriving workforce because of the way employees perceive and evaluate the embedded challenges. By applying CAT to algorithmic HRM contexts, our study advances beyond existing literature demonstrating that AI-employee collaboration functions as a cognitive enhancer, empowering employees to approach challenges with positivity and confidence. Second, this study advances our understanding of the underlying mechanisms that translate the potential implications of AI-employee collaborations for employee thriving. The findings suggest that CAT (Lazarus & Folkman, 1984 and 1987) can be extended to cover digital AI-driven contexts, where

technology not only restructures workflows but also shapes employees' perceptions and appraisals of challenges. This research reveals that AI-employee collaboration has the potential to act as a catalyst for positive challenge appraisals, enabling employees to perceive their roles and tasks as opportunities for growth and learning. This perspective moves beyond the existing narrative that often frames AI as a threat (Zhou et al., 2023; Fleming, 2019), instead positioning it as a transformative tool that fosters resilience, adaptability, and continuous development in the workplace. By integrating CAT to study AI-employee collaboration, this research provides a novel lens for understanding employee thriving in technologically advanced work environments

Third, this study contributes to the literature with a more nuanced picture about the conditions under which challenge appraisal as a result of AI-employee collaboration is most beneficial for employee thriving. Our finding highlights the importance of employee connectivity in enhancing the positive effects of challenge appraisal on thriving, suggesting that social resources and networks are integral to thriving in the digital workplace (Porath et al., 2012; Carmeli & Spreitzer, 2009). The findings imply that organizational support systems, including technology resources and peer networks, are crucial in creating a conducive AI-driven work environments where employees can thrive. Moreover, the study demonstrates the strategic importance for organizations to design work environments that foster positive appraisals of challenges and strong employee connectivity, leveraging technology as a means to enhance employee thriving. By so doing, this research expands the CAT's scope to the HRM complexities in the algorithmic era, showing new variables and mechanisms at play in the cognitive appraisal process. Our findings suggest that theoretical models should consider the social dimensions of work in increasingly technologically integrated algorithmic work environments, emphasizing the importance of social support

systems and employee connectivity in maximizing the benefits of employee-technology collaboration for employee thriving.

6.2 Practical Implications

Collaborating with AI tools can foster a perception of growth opportunities and enable problem-solving among employees by reducing repetitive tasks and allowing them to focus on more strategic and creative aspects of their work. To ensure the success of such collaboration, organizations should provide comprehensive and tailored training programs (Klein & Heuser, 2008). These programs should be designed to address the specific needs of employees, the context in which the AI tools are deployed, and the ways AI-employee collaboration modifies workflows, ensuring that the transition is seamless and enhances, rather than undermines, the overall employee experience. For example, skill-specific training can highlight how AI complements individual expertise. Scenario-based learning can demonstrate how AI improves task efficiency in real-world work contexts.

Additionally, organizations must establish dynamic feedback loops that actively involve employees in the AI integration process (Makarius et al., 2020). These loops should provide employees with opportunities to express how AI collaboration influences their perception of challenges, and engagement with their roles. This iterative feedback loop will ensure that employees view AI as an enabler of meaningful work rather than a threat to their roles or autonomy. This strategy will also help to enhance business productivity, and support employees' professional growth, and thriving in the workplace.

Organizations should design and implement comprehensive AI adoption strategies that emphasize AI's role in creating meaningful, challenging, and rewarding work experiences for employees (Chowdhury et al., 2023). These strategies should clearly articulate how AI tools are not merely instruments of efficiency but enablers of human creativity, problem-solving, and skill enhancement. By creating an environment where

employees feel empowered to tackle challenging and meaningful work with the support of AI, organizations can foster a sense of engagement, energy, and purpose, which are key components of thriving. This empowerment can also foster a culture of innovation, as employees view AI as a tool for exploration and creativity rather than a disruptor.

Strong interpersonal connections at work will enhance the positive effects of challenge appraisal on employee thriving. This sense of connectivity fosters a culture of collaboration, trust, and shared purpose, amplifying the overall impact of challenge appraisal on employee thriving (Hargadon, 2006). Therefore, to strengthen employee connectivity, organizations should implement a combination of team-building activities, community forums, and structured peer support systems (Cross et al., 2018). These initiatives will help to create a sense of belongingness and collective action among employees, reinforcing their ability to navigate and thrive in dynamic work environments. Organizations should encourage cross-functional teams to work on projects involving AI tools, allowing employees to collectively explore, learn, and adapt to new technologies. This shared learning can help strengthen relationships and build both trust and familiarity in both the tools and their peers. The experience will help support employees' personal and professional growth, ensuring they feel motivated, energized, and resilient in thriving and navigating a rapidly changing digital work landscape.

7. Conclusion

The relationship between AI-employee collaboration, employee thriving, and the role of challenge appraisal offers a nuanced understanding of the interplay between technology, individual cognition, and workplace outcomes. The findings emphasize the importance of creating workspaces where AI is thoughtfully integrated as a catalyst for professional

development, continuous learning, and positive organizational change. Algorithmic management stemming from AI-employee collaboration challenges traditional notions of teamwork and decision-making by introducing AI as a non-human collaborator in roles historically occupied by humans. This integration adds new dimensions to the concept of employee thriving in the workplace

This research paves the way for a new era of HRM development, where algorithmic technology and human expertise converge to create thriving workplaces. By rethinking the role of AI in shaping employee experiences, the research advocates for a holistic approach that balances technological progress, employee thriving, and the conditions necessary for fostering employee thriving.

Limitations and Future Research Directions

We acknowledge the limitations of this study, and we see them as providing opportunities for further research. First, although we utilized the G*Power tool to evaluate the adequacy of the sample size, which supported our decision to draw from 214 samples, we invite future research to expand the sample size above this recommended size by G*Power. Second, this study is cross-sectional in nature, and we are cautious of making any causality related claims. We have undertaken several measures to reduce common method bias and to enhance reliability and validity of our research. Nonetheless, we invite future research to employ an alternative, longitudinal design that could enable the collection of data over time. This would be better suited to address causality-related predictions, further enriching knowledge about AI-employee collaboration and employee thriving. Third, we focus primarily on challenge appraisal, rather than hindrance appraisal given the widely acknowledged threats posed by emerging technologies like AI. Therefore, by introducing challenge appraisal to the discourse, our research helps to highlight that even though there are challenges, it is also likely that employees perceive them as opportunities for mastery and

growth, presenting a positive outlook. Fourth, AI-employee collaboration has so far been treated as referring to the integration of AI technologies, without differentiating types of AI tools/systems. Future research could explore the distinct impacts of various AI tools, comparing their relative importance in influencing key employee outcomes.

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Figure 1: Theoretical Model

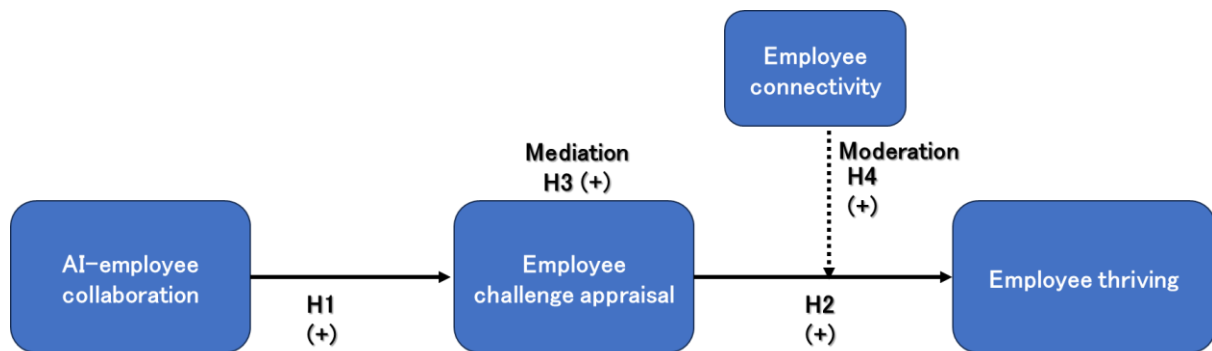


Figure 2: Interaction of employee challenge appraisal and connectivity on thriving

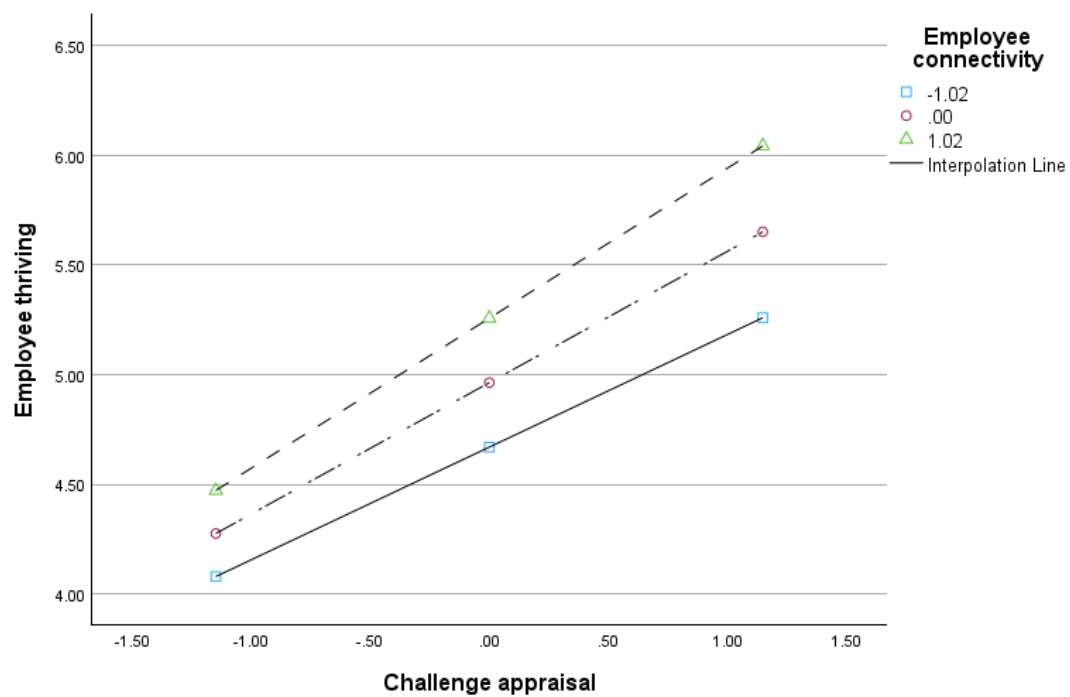


Table 1: Response checks and total sample

Items	Key Figures
Target Sample Size	280
Failed screening check	28
Failed attention checks	32
Incomplete response	6
Eligible Responses	214 (sample adequacy statistically tested and is greater than the required sample) – G power test
Using/Seeking assistance from AI (as a team member/assistant)	214 Tools include different generative AI chatbots, IBM Watson, Tableau, AWS Cloud AI, Forecasting apps, inhouse AI prediction systems, people analytics tools, business intelligence and simulation software

Table 2: Sample characteristics

	20-35	36-45	46-55	55 +	
Age	69	62	54	29	
	Bachelors	Masters	Doctorate	Other diploma	
Education	84	74	12	44	
	Male	Female	Other		
Gender	108	87	21		
	Marketing/Retail	Hospitality	Finance	Manufacturing	IT
Sector	70	57		39	48

Table 3: Common method bias and collinearity test

		1	2	3	4	5
1	AI-employee collab		1	1.241		
2	Challenge appraisal			1.683		
3	Thriving					
4	Connectivity			1.534		
5	Marker variable	1.23	2.37	2.336	1.516	

Note: Marker variable: consumer green purchase intention

Table 4: Descriptive and reliability statistics

		Mean	SD	Alpha	CR	AVE	1	2	3	4
1	AI- employee collab	4.87	1.169	0.85	0.86	0.626	<i>0.791</i>			
2	Challenge appraisal	5.436	1.147	0.916	0.921	0.857	0.416	<i>0.926</i>		
3	Thriving	5.015	1.164	0.956	0.957	0.694	0.396	0.733	<i>0.833</i>	
4	Connectivity	5.437	1.02	0.935	0.939	0.723	0.224	0.538	0.549	<i>0.85</i>

Note: No = 214; entries in bold and italics indicate square roots of AVEs

Table 5: Results of hypothesis testing

		coeff	SE	t	p-value	LLCI	ULCI	Results
H1	AEC→ECA	0.39	0.0618	6.307	0.001	0.268	0.511	Accepted
H2	ECA→ETH	0.685	0.053	12.865	0.001	0.58	0.79	Accepted
Direct effect	AEC→ETH	0.105	0.052	2.033	0.042	0.003	0.207	
Mediation H3		Effect	BootSE	BootLLCI	BootULCI			Results
Indirect effect	AEC→ECA→ETH	0.267	0.058	0.157	0.388			Accepted
Moderation H4		coeff	SE	t	p-value	LLCI	ULCI	Results
Interaction	ECN on ETH	0.0836	0.036	2.337	0.02	0.013	0.154	Accepted
Test(s) of highest order unconditional interaction(s)	R2-change	F	df1	df2	p			
ECH*ECN	0.011	5.463	1	205	0.02			
Conditional effects of the focal predictor (ECH) at values of the moderator (ECN)	ECN	Effect	SE	t	p-value	LLCI	ULCI	
	-1.019	0.513	0.063	8.112	0.001	0.389	0.639	
	0	0.599	0.059	10.041	0.001	0.482	0.717	
	1.019	0.684	0.076	9.012	0.001	0.535	0.834	
Moderated Mediation		Index	BootSE	BootLLCI	BootULCI			
	ECN	0.033	0.018	0.002	0.071			

Table 6: Control variables analysis

	Co-eff	SE	t	p-value	LLCI	ULCI
Age →thriving	0.207	0.46	0.451	0.653	-0.07	0.112
Education →thriving	-0.031	0.482	-0.681	0.497	-0.122	0.059
Gender →thriving	-0.037	0.816	-0.459	0.647	-0.198	0.124
Sector →thriving	0.028	0.393	0.729	0.467	-0.048	0.103
Age → challenge	-0.043	0.062	-0.683	0.496	-1.666	0.804
Education →challenge	0.039	0.068	0.624	0.533	-0.084	0.162
Gender →challenge	-0.111	0.109	-1.012	0.313	-0.326	0.105
Sector →challenge	0.096	0.052	1.852	0.066	-0.006	0.197

Appendix 1

Numerals at the end of each item is the item loading

7-point Likert-type scale ranging from 1 = strongly disagree to 7 = strongly agree

Items measuring AI-employee collaboration (Kong et al., 2023)

In my workplace,

I collaborate with AI tools in my decision-making process.

I collaborate with AI tools in my prediction process (making judgements, foresight). 0.749

I collaborate with AI tools in my problem-solving process. 0.726

I collaborate with AI tools in my information identification and evaluation process. 0.807

I collaborate with AI tools in my problems, opportunities, or risk recognition process. 0.837

Items measuring challenge appraisal (LePine et al., 2016)

Working to fulfil the demands of collaborating with AI tools in my job helps to improve my personal growth and well-being. 0.897

I feel the demands of collaborating with AI tools in my job challenge me to achieve personal goals and accomplishment. 0.935

In general, I feel that collaborating with AI tools in my job promotes my personal accomplishment. 0.944

Items measuring employee connectivity (Carmeli & Spreitzer, 2009)

In my workplace,

We have very open relationships. 0.744

We are always open to listening to our coworkers' new ideas. 0.852

We are very open to diverse influences, even if they come from unconventional sources, such as new employees, customers, etc. 0.864

We are attentive to new opportunities that can make our system more efficient and effective. 0.834

The relationships we have enable us to generate new things. 0.900

The relationships we have enable us to learn new things. 0.892

The relationships we have encourage us to seek out new opportunities. 0.857

Items measuring employee thriving (Carmeli & Spreitzer, 2009)

To what extent do you learn new things at work. 0.707

To what extent do the things you learn at work help you in your life. 0.794

To what extent do the things you learn at work enable you to thrive in life. 0.782

I feel active and energetic at work. 0.810

I have high energy to complete my work. 0.876

During the working day I feel I am full of energy. 0.849

I have the energy to successfully do my job (vitality). 0.856

When I come to work in the morning I have energy for the new day. 0.768

I feel a lot of excitement when I am doing my work. 0.892

The work in this organization gives me positive energy. 0.894

When I am at work, I feel vital and alive. 0.900

Items measuring marker variable consumer green purchase intention (Chen & Chang, 2012)

Alpha = 0.915, composite reliability = 0.921, AVE = 0.797

Environmental protection is important to me when making product purchases. 0.871

I believe that green products help to reduce pollution (water, air, etc.). 0.907

I believe that green products help to save nature and its resources. 0.917

Given a choice, I will prefer a green product over a conventional product. 0.876