Humanizing GenAI at Work: Bridging the Gap Between Technological Innovation and Employee Engagement

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ABSTRACT

Purpose

This paper seeks to explore the influence of Generative AI (GenAI) on employee performance in the workplace, viewed from a managerial perspective. It concentrates on key elements such as employee engagement, trust in GenAI, and attitudes towards its implementation. This exploration is motivated by the ongoing evolution of GenAI, which presents managers with the crucial task of understanding and integrating this technology into their strategic frameworks.

Methodology

We collected 251 responses from managers and senior managers representing companies that have embraced GenAI in Spain. Hierarchical regression analysis was employed to examine the hypotheses. Subsequently, mediating effects and moderated mediation effects were scrutinized using the bias-corrected bootstrapping method.

Findings

The data analysis suggests a significant enhancement in employee engagement and performance from a managerial perspective, attributed to improved attitudes and trust towards the adoption of GenAI. This conclusion is drawn from our research conducted with samples collected in Spain. Notably, our findings indicate that while positive attitudes towards GenAI correlate with enhanced engagement and performance, there exists a weakening effect on the significant positive impact of GenAI adoption in the workplace. This suggests that GenAI is still in its early stages of adoption within these companies, necessitating additional time for managers to develop greater confidence in its efficacy.

Originality/value

This study represents one of the pioneering investigations centred on the implementation of GenAI within the workplace context. It contributes significantly to the existing body of literature concerning the Stimulus–Organism–Response model in technology innovation adoption within work environments.

Research Paper

Keywords: GenAI, management, work engagement, technology acceptance, employee performance

Introduction

The integration of artificial intelligence (AI) into various aspects of business management has been one of the most transformative trends in the modern corporate world (Murray, 2015). Among various AI technologies, Generative AI (GenAI) stands out due to its unique ability to create new content, predict outcomes, and automate complex tasks. In this regard, as GenAI continues to advance, managers are faced with the challenge of understanding and integrating general AI into their strategic vision. Particularly noteworthy is its application and changing landscape in Human Resource Management (HRM), where it has begun to reshape traditional practices and strategies (Holzinger *et al.,* 2018). From recruitment and talent acquisition to personalized training and development programs, GenAI is revolutionizing how HR departments acts. Managers in this space must not only consider the technical and operational aspects of GenAI integration but also the profound human capital implications because this technology is not just an operational tool; it represents a shift in how organizations approach their most valuable asset – their employees (Budhwar, *et al*., 2023).

However, with this change comes the need to understand and address how employees perceive and interact with these advanced technologies (Braganza, *et al*., 2021). Thus, managers need to anticipate the skills landscape and adjust their workforce strategies accordingly because the employee perspective is crucial as it significantly influences their engagement, productivity, and overall performance within the organization. Currently, it remains uncertain whether artificial intelligence presents an opportunity or a threat to workers (Nam, 2019). On one hand, AI has the capacity to enhance job engagement and satisfaction (PwC, 2018a) while augmenting worker input. On the other hand, it may lead to job displacement and instill fear of unemployment (Mokyr *et al*., 2015), thereby potentially demotivating workers. To tackle with these psychological aspects, managers have also deal with employee perceptions and attitudes towards GenAI because it can significantly affect its acceptance and utilization in the workplace.

The introduction of GenAI in HRM raises several pertinent questions. How do employees perceive the role of AI in their professional environment? Does the reliance on AI for HR decisions affect their engagement and sense of belonging in the organization? And most importantly, how does the trust in and attitude towards GenAI impact employee performance?

Drawing on the stimulus-organism-response framework (S-O-R), technology acceptance model (TAM) and technology readiness model (TRI), we aim to explore the relationship between GenAI and employee performance from a managerial point of view. This research examines the essential factors such as employee engagement, trust in AI, and attitudes towards its adoption. Drawing from existing literature and relevant studies, the analysis seeks to light perceptions of GenAI and its impact on the workforce performance. The remainder of the article is organized into four distinct sections. Section 2 introduces the theoretical framework and provides a literature review on GenAI. The methodology is discussed in Section 3, while the results are presented in Section 4. Finally, Section 5 concludes the paper with recommendations and suggestions for future research.

Theory and Hypotheses

(S-O-R) framework

Mehrabian and Russell's (1974) S-O-R framework, one of the most influential models in environmental psychology and user behavior studies, elucidates the impact of the environment on human behavior (Peng and Kim, 2014; Luqman *et al*., 2017; Sultan *et al*., 2021). The authors identified that the environment (stimulus) external to consumers influences their inner states (organism), subsequently affecting behavioral intentions (response). While previous studies primarily focused on physical environmental factors for the stimulus component of the S-O-R framework, it is suggested that staff interaction should also be considered to explain overall service quality. Thus, the S-O-R framework comprises three components: stimulus (input), organism (processes), and response (output).

This theoretical framework was widely used in previous research related to Artificial Intelligence (Nazir et al., 2023, Chen et al., 2022). It is a way of understanding how external factors influence human behavior (eg. use a new technology), focusing on how individuals process and respond to environmental stimuli. So, the S-O-R framework offers a lens through which to examine the adoption of GenAI, a new technological tool characterized by cognitive and emotional dimensions.

In this paper, we extend the S-O-R framework to include attitudes towards AI, trust, and work engagement as key stimuli. These factors play critical roles in the adoption of GenAI, particularly in its early stages. Additionally, our framework is grounded in the perceived usefulness of GenAI as an organism. The response would be the employee's performance, thus influenced by managerial implementation of these tools. Therefore, the response within the S-O-R framework encapsulates productivity, encompassing both output quality and time saved. The readiness to embrace GenAI in daily work tasks is influenced by employees' emotional responses, which can be positive, negative, or neutral towards certain stimuli related to GenAI adoption at work, such as attitudes, trust, or engagement. These emotional responses directly affect the utilization of GenAI (Organism) and its impact on workplace practices.

TRI Model and TAM

According to TRI model proposed by Parasuraman (2020, p. 307): “The technology-readiness construct refers to people’s propensity to embrace and use new technologies for accomplishing goals in home life and at work. The construct can be viewed as an overall state of mind resulting from a gestalt of mental enablers and inhibitors that collectively determine a person’s predisposition to use new technologies.” Particularly, technological optimism represents “a positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives” (Parasuraman and Colby, 2015, p. 60). Optimists accept situations and are more willing to use new technologies (Lu *et al*., 2012), perceiving them as functional and trustworthy, overlooking possible negatives outcomes, than are pessimistic technology users (Walczuch *et al*., 2007). Thus, optimistic employees are more positively predisposed toward new technologies.

Using the TRI framework, we assess the extent to which employees are willing to adopt a new technology in their daily work. There are not many prior studies utilizing the TRI framework to identify whether the adoption of artificial intelligence differs from the adoption of previous technological innovations (Flavian *et al*., 2022). Our study provides results indicating that employees effectively apply (are more productive) these GenAI tools when they have a positive attitude towards them, confidence, and are engaged employees. In this way, they find these tools useful and integrate them into their work.

On the other hand, Davis (1989) and his colleagues were investigating the TAM, a theoretical framework aimed at comprehending the acceptance, adoption, and utilization of novel technologies. TAM delineates two fundamental constructs that encapsulate the user's interaction with technology: perceived ease of use and perceived usefulness. For example, features such as the curiosity about usage and potential of the tools, which are in turn intuitive interfaces, enhance individuals' perception of GenAI. This leads to positive attitudes and intentions towards its adoption and usage. Therefore, this TAM model is highly suitable for predicting and promoting the acceptance and adoption of GenAI in various environments. has been widely used and recommended in the context of GenAI (Gupta *et al*., 2024; Mogaji *et al*., 2024)

In this paper, Figure 1 extends the S-O-R framework to include attitudes towards AI, trust, and work engagement as key stimuli. These factors play critical roles in the adoption of GenAI, particularly in its early stages. Additionally, our framework is grounded in the perceived usefulness of GenAI as an organism. The response would be the employee's performance, thus influenced by managerial implementation of these tools. Therefore, the response within the S-O-R framework encapsulates productivity, encompassing both output quality and time saved. The readiness to embrace GenAI in daily work tasks is influenced by employees' emotional responses, which can be positive, negative, or neutral towards certain stimuli related to GenAI adoption at work, such as attitudes, trust, or engagement. These emotional responses directly affect the utilization of GenAI (Organism) and its impact on workplace practices. So, this variable can affect in the S-O link. The specific attributes of GenAI interact with the constructs of the S-O-R framework and the TRI and TAM model by influencing individuals' perceptions, attitudes, and behaviors towards technology, which in turn affects its adoption and usage in the workplace environment.

- Insert Figure 1 about here -

Generative Artificial Intelligence

The literature on GenAI in organizational dynamics explores its broad impact, including enhancing stakeholder relationships and improving wellbeing, with McKinsey (2017) and Edlich et al. (2018) highlighting its transformative potential in HRM. Depending on its use, GenAI can provide on-demand personalized support delivering innovative responses to complex queries and offering guidance on a wide array of topics (Hatzius *et al*., 2023). In this context, AI can significantly boost human workers leading to increased motivation, job satisfaction and employee performance (Cheng et al., 2022; Milanez, 2023). In the same line, the OECD survey reveals AI's impact, indicating GenAI's potential to streamline operations and elevate employee performance. On the contrary, concerns persist regarding job displacement and unemployment highlighting the need for further research on the implications of GenAI. (Arntz *et al*., 2016; Mokyr *et al*., 2015).

In this regard, the rapid implementation of GenAI within work environments is ready to change the way employees are working towards more autonomous work methodologies. Consequently, it is important to address inquiries regarding the potential benefits of heightened worker autonomy on the quality of employment outcomes, as well as the role GenAI plays in this scenario (Braganza, 2023). The introduction of GenAI within an organization "enhances organizational capacity and triggers various shifts in employee behaviors and expectations" (Pluta and Rudawska, 2016, p. 294).

Usefulness

The perception of the usefulness of technologies from the employee perspective significantly influences the adoption and effectiveness of workplace performance. When employees view the implementation of new technologies, such as AI, as a useful tool that simplifies their daily tasks and enhances their capabilities, they are more likely to incorporate them into their routines (Chatterjee *et al*., 2021; Kong *et al*., 2023). In this regard, this positive perception stems not only from the practical benefits of the technology but also from the empowerment employees feel when they can engage more meaningfully in their work (Kong *et al*., 2023).

Tools that are intuitive and easy to integrate into existing workflows encourage wider adoption among employees (Bankins *et al*., 2023). In this context, Holden and Rada (2011) stated that perceived usability of technologies is positively correlated with favorable attitudes and behaviors toward them; thus, it reduces technology-related anxiety and resistance, facilitating a smoother transition and quicker benefits from new tools. Kelly *et al*. (2023) found that perceived usefulness and low effort expectancy significantly and positively predict attitudes and use behavior of AI across multiple industries. In this regard, Kashive *et al*. (2021) stated that the effect of AI adoption on employee behavior is stronger when the worker perceives it as useful. However, Chatterjee *et al*. (2021) concluded that when the level of technical sophistication is not high or when technologies are widely used, perceived usefulness might become a weak predictor of technology acceptance, leading to perceptions of technology as useless.

Attitude towards AI

The synergy between human workers and AI technology significantly impacts job performance. Nguyen and Malik (2022) found that employee satisfaction with AI, particularly regarding its performance and alignment with users' needs, positively influenced employee performance. Similarly, Marikyan *et al*. (2022) highlighted a direct correlation between these satisfaction levels and enhanced employee performance. Furthermore, the perception of AI as an effective tool for repetitive tasks (Sowa *et al*., 2021), specialized functions (Sowa and Przegalinska, 2020), and as a decision-making aid (Kawaguchi, 2021), fosters a valuable task-technology fit.

Despite the benefits, Tong *et al*. (2021) address the fear-based attitudes towards AI, noting their potential to hinder the adoption of AI technologies. These fears stem from concerns about job replacement (Lingmont and Alexiou, 2020; Suseno *et al*., 2022), skill obsolescence (Innocenti and Golin, 2022), and drastic changes to current work practices (Brougham and Haar, 2020). These attitudes lead to reduced organizational commitment, diminished work engagement, and heightened perceptions of job insecurity, often culminating in increased turnover intentions, burnout, and resistance to change (Arias-Pérez and Vélez- Jaramillo, 2022; Suseno *et al*., 2022). However, these effects can be moderated by individual and organizational factors, potentially leading to increased commitment and performance.

In this regard, individual characteristics significantly shape employees' attitudes towards AI. Ding (2021) demonstrates that employees who perceive AI as a challenge rather than a hindrance are likely to adopt proactive strategies, resulting in increased work performance. Leonard and Tyers (2021) further explore how workers' agency, influenced by their organizational role and personal attributes like age and career stage, affects their interaction with AI. Koo *et al*. (2021) and Cao *et al*. (2021) reveal that employees often hold mixed views about AI, balancing its perceived benefits and drawbacks. Based on the literature reviewed, we are led to propose the following hypothesis:

Research suggests that employees with prior experience using AI are more likely to have positive attitudes towards these technologies, which can enhance their work engagement (Noy, 2023; Wijayati, 2022). This is supported by evidence showing that AI tools can increase productivity and improve employee performance, particularly for novice and low-skilled workers (Brynjolfsson, 2023). Besides, it has been found that AI can help employees perform tasks more efficiently and organized, leading to increased work engagement. Automating certain work tasks using AI can reduce the risk of manual errors, leading to less stress and workload for employees (Sari *et al*., 2020). However, it can also lead to stress and mental health issues in employees due to the creation of a boundless time and space work environment (Malik *et al*., 2021)

H_1: The attitude towards GenAI has higher influence on employee performance among employees who have already used these technologies and found them useful.

Trust

Trust in AI is essential for its successful integration into work environments, as it fosters employee acceptance and engagement with the technology (Kim *et al*., 2021). In addition, trust in AI is a multidimensional construct, including trust in functionality, reliability, and data protection, and it can lead to innovative use of AI tools like chatbots in the workplace (Wang *et al*., 2023).

The correlation between trust and performance, as highlighted by Lee *et al*. (2018), is particularly relevant when considering AI technologies. This trust is not merely in the AI's functionality but in its role as a tool that supports and enhances their work, without posing a threat to their job security and professional growth. In this regard, Yadav *et al*. (2022) emphasized that trust is central to the employee-employer relationship. Extending this to AI, employees must view AI systems as integral, trusted components of their work environment facilitating not only integration of AI into daily operations but also raising a culture of innovation and adaptability. In this context, when employees trust in the AI's capabilities, they are more likely to engage deeply with their work turning to increase employee performance. Additionally, Chowdhury *et al*. (2022) and Chowdhury *et al*. (2023) emphasize the role of trust in AI, understanding its purpose, and the development of requisite skills as foundational for successful human-AI collaboration.

However, the absence of genuine emotions in current AI systems may impact interpersonal trust, which is essential for work engagement with the role of institutional trust (Spandaro *et al*., 2020). Moreover, to boost trust in GenAI and subsequently enhance employee engagement, organizations can prioritize ethical frameworks aimed at ensuring AI reliability and safety, which have been demonstrated to foster trust among employees (Glikson and Woolley, 2020). In this sense, Chen *et al*. (2023) posit that the successful adoption of AI in the workplace depends on the trust users have in the tool. If they believe that AI tools are reliable they are more open to utilizing them leading to more innovative approaches to tasks. Furthermore, the positive relationship between trust and performance in this context, as evidenced by the research of van den Heuvel *et al*. (2016). Their study, which analyzed data from almost 700 companies, demonstrated that employee performance increases when there is trust in the changes being implemented. Applied to AI, this suggests that when employees trust in the AI tools provided to them, they are more likely to be engaged with and supportive of the organizational changes these tools bring about. Therefore, the following hypotheses are presented:

H_2: Trust on GenAI has higher influence on employee performance among employees who have already used these technologies and found them useful

Employee engagement

The concept of employee engagement has garnered significant attention (Bal *et al*., 2013; Lin, 2010; Rayton *et al*.,2012; Saks, 2006). The terms employee engagement and job engagement are often used synonymously, typically understood as employee behaviors that contribute to an organization’s success and financial improvement (Bates, 2004; Richman, 2006). Saks (2006, p.602) describes engagement as ‘an unique experience encompassing cognitive, emotional, and behavioral elements that influence how an individual performs their role’. Employees who are highly engaged in their work usually have a stronger bond with their organizations and perform their tasks with more vigor (Schaufeli and Salanova, 2007).

Integrating AI into the workplace implicates not just a technological shift but a strategic one that impacts employee engagement and performance (Mittal, 2023). The successful adoption of GenAI is dependent on how managers and employees perceive its usefulness, which in turn is significantly influenced by the level of employee engagement (Wijayati, 2022). In this context, studies suggest the need for managers to play an active role in ensuring a positive integration experience, balancing the technological and human aspects of AI integration. In this regard, the integration of innovative technologies in the workplace has been shown to increase employee engagement when managed properly (Nisha, 2022). Thus, managers play a crucial role in this aspect by ensuring that AI is not just implemented, but integrated in a way that aligns with the employees' work and the organization's goals. If it appears and employees feel that technology is useful, easy to use and improves their daily work, providing opportunities for professional development, and enhancing the quality of their job tasks; then the employee performance will increase (Gomathy, 2022).

In this line, there is a consensus among scholars that employee engagement has a significant impact on employee performance (Harter *et al*., 2002; Rich *et al*., 2010; Lu and Gursoy, 2016) due to employees being more involved in their tasks and daily work (Suhartanto *et al*., 2018; Kahn, 1992). Employees with higher engagement levels have more satisfaction with self-actualization to their organization (Eldor and Vigoda-Gadot, 2017) and are more connected to their work with a higher-level energy and connectivity that enable them to identify themselves with their work (Schaufeli and Salanova, 2007). Furthermore, highly engaged employees have a positive impact on lower turnover rates (Lu *et al*., 2016), higher customer satisfaction, and improved profitability (Harter *et al*., 2002; Richman, 2006). Conversely, it has been observed that employees who exhibit lower levels of job engagement are more likely to disengage from the organization altogether (Yalabik *et al*., 2013). Considering all the previously mentioned, work engagement has been shown to yield positive outcomes for both employees and organizations, resulting in enhanced individual-level performance (Bedarkar and Pandita, 2014). In line with this, we propose the following hypothesis:

H_3: Employee engagement has higher influence on employee performance among employees who have already used these technologies and found them useful.

Methods

Sample and procedure

The objective of this project is to gauge managers' perspectives on the effectiveness of utilizing GenAI to enhance employee performance standards. The survey was structured into seven segments, encompassing demographic details and six sections built upon the S-O-R framework elements such as attitude, trust, engagement, GenAI, usefulness, and performance metrics. This research has collected survey samples across various sectors, including technology, education, finance, hospitality, and health in Spain. Over two months period, this online survey has been distributed to over 2500 managers with a total of 251 valid responses, which leads our response rate to 10%. This is acceptable for online survey such as the presented in this study as stated by Mellahi and Harris (2016).

The average age of respondents was 36 years (with a standard deviation of 11.124), with 40% holding director-level positions and 28% saving as senior managers (see Figure 2). Furthermore, 51.4% of respondents identified as male, and 16.7% hailed from the high-technology industry.

- Insert Figure 2 about here -

The results highlight that only 13.9% of the sampled managers reported frequent use of AI, while 36.7% indicated rare utilization (See Figure 3).

- Insert Figure 3 about here -

With 85% of the respondents hailing from medium and large companies, it's worth noting that the dataset predominantly represents the Spanish market, owing to the prominence of local market insights.

Analysis strategy

The scales utilised to measure all items were based on a five-point Likert scale, with 1 indicating "strongly disagree" and 5 indicating "strongly agree." The primary measurements employed in this study were adapted from English articles. To streamline the data collection process and ensure ease of understanding for Spanish participants, the survey questions were translated into Spanish. This translation process adhered to established cross-cultural translation procedures as outlined by Brislin (1980).

To assess GenAI, we used the three items developed by (Parasuraman, 2000; Parasuraman and Colby, 2015). Sample items include "GenAI tools help improve my quality of work" and "GenAI tools give me more control over my work tasks." The Cronbach's alpha was 0.87.

We measured usefulness using an adjusted set of six items developed by (Davis, 1989). Sample items include "I am enthusiastic about my job" and "I persist in my work with perseverance, even when things are not going well." The Cronbach's alpha was 0.88.

Attitude towards AI was measured using four items adapted from (Parasuraman 2000; Parasuraman and Colby, 2015) research. Sample items in the questionnaire included "Other people come to me for advice on new technologies" and "I'm generally among the first in my circle of friends to pick up a new GenAI technology when it comes out." The Cronbach's alpha was 0.87.

Trust in AI was assessed using six items developed by (McKnight *et al*., 2002; Glikson and Woolley, 2020; Frank *et al*., 2023; Candrian and Scherer, 2022). Sample items include "I feel comfortable with the information GenAI provides me" and "I trust GenAI in my work." The Cronbach's alpha was 0.88.

Employee performance was tested through a three-item scale adapted from (Wijayati *et al*., 2022). Sample items include "My performance meets what is requested from me," "My work meets the expectations of the organisation in a professional way" and "My tasks are usually completed on time." The Cronbach's alpha was 0.83.

Employee engagement was measured using six items adapted from previous studies (Wijayati *et al*., 2022; Hakanen *et al*., 2008). Sample items include: "I am enthusiastic about my job," "At my work, I always persevere, even when things do not go well," and "When I am working, I forget everything else around me." The Cronbach's alpha was 0.89.

Analytical strategy

This study considered Podsakoff *et al*. (2003) recommended and conducted confirmatory factor analysis (CFA) via Amos 29 to test the validity of the study variables. The maximum likelihood estimator in SPSS (Muthen *et al*., 2017) was used for analysis. All paths correspond to freely estimated parameters, and all the goodness of fit indexes, such as Chi-square (χ^2), CFI, SRMR, TLI, BIC, RMSER, GFI and AGFI used in our model (Hu and Bentler, 1999). We followed Preacher *et al*.'s (2007) recommended methodology, utilizing bootstrapping resampling with 50,000 resamples. Our analysis employed the PROCESS macro V4.2 of SPSS29 developed by Hayes (2022), specifying model 7, and arranged the independent, mediator, and dependent variables accordingly within the bootstrapping analysis dialog boxes. The bias-corrected confidence intervals were set at 95%.

Results

Confirmatory Factor Analysis (CFA) was performed to validate the hypothesized three factors (Trust, Attitude, and Employee Performance) concerning the impact of GenAI on employee performance, as perceived by managers regarding technology usefulness. Our results of the model good fit shows that all variables are valid ($\chi2$ =1211.348, df =721, CFI=0.91, TLI=0.90, RMSEA =0.06, and SRMR=0.06.

Descriptive statistics

Our data analysis yielded the means, standard deviations, bivariate correlations, and reliabilities of the variables. The results indicate that all main themes are correlated but independent enough to demonstrate that the research model was free of multicollinearity and so it was safe to proceed with modelling.

- Insert Table I about here -

Focusing on the specific results presented in Table I, when focusing on GenAI and its correlation among all the variables studied, the results indicate a strong positive correlation suggesting that, higher ratings of GenAI are associate with higher perceived usefulness (.635); better attitudes (.502) and higher trust (.661) towards this type of technology; and higher levels of employee engagement (.400) and performance (.421). One of the highest correlations presented in Table 1 is the association between usefulness and Trust (.691) indicating that perceptions of usefulness and trust in GenAI are closely linked.

Overall, these results suggest that positive perceptions of GenAI (in terms of its usefulness, the trust employees place in it, and general attitudes) are associated with better employee engagement and performance outcomes. This implies that acceptance and trust in technological tools like GenAI are variables to be considered in how effectively these tools enhance workplace outcomes.

Hypothesis testing

The hypotheses were tested using hierarchical regression analysis across three different models (M1, M2, and M3) to evaluate the relationship between trust, attitude, and employee engagement towards employee performance, considering GenAI as a moderator and usefulness as a mediator for these relationships. Each model tests different relationships and effects, including direct effects, moderation, and mediation. The model fit for M1 shows high overall model fit with an R^2 of 0.65, explaining 65% of the variance in the dependent variable. The substantial change in R^2 ($\Delta R^2 = 0.43$) with the inclusion of moderators and mediators indicates their importance. M2 presents an excellent model fit with an R2 of 0.72, suggesting that 72% of the variance is explained by the model; finally, M3 presents a good model fit with an R^2 of 0.63 (see Table II).

- Insert Table II about here -

The results indicate significant interactions between all independent variables—attitude, trust, and employee engagement—and the dependent variable, employee performance, with positive coefficients observed. The models consider attitude (M1), Trust (M2) and Employee engagement (M3) as the independent variable and GenAI and Usefulness as the mediator and moderator, respectively. Results indicates that Attitude toward usefulness ($\beta = 0.43$, $p < 0.01$), trust toward usefulness ($\beta = 0.73$, $p < 0.05$) and employee engagement toward usefulness ($\beta = 0.28$, $p < 0.05$) significantly predicts the dependent variable, suggesting a strong positive relationship. GenAI demonstrated a positive and significant connection with usefulness in all the three models when considering this variable alone in each individual model (M1: $\beta = 0.69$, $p < 0.01$; M2: $\beta = 0.49$, $p < 0.05$; M3: $\beta = 0.68$, $p < 0.01$). Lastly, usefulness exhibited a positive relationship toward employee performance (M1: $\beta = 0.27$, $p < 0.05$; M2: $\beta = 0.22$, $p < 0.05$; M3: $\beta = 0.54$, $p < 0.01$) indicating that this variable operates as a mediator of the studied variables indicating some influence of each independent variable on performance.

Finally, it is worth to mention that the interaction between GenAI and the independent variables are not statistically significant, for trust and employee engagement suggesting no moderation effect of GenAI on the relationship between these variables and employee performance.

Overall, attitudes toward GenAI had a significant negative effect, indicating that GenAI weakens the significant positive impact of attitudes on usefulness, supporting H1 ($\beta = 0.06$, $p < 0.05$,). Figure 4 illustrates the interaction effects of attitude and GenAI on usefulness.

- Insert Figure 4 about here -

Contrary to expectations, the results of the present study indicate that GenAI does not moderate the significant impact of trust (H2) and employee engagement (H3) on usefulness. The interaction terms, Gent X Trust (H2) with $\beta = -0.06$, $p > 0.1$, and Gent X employee engagement (H3) with $\beta = -0.03$, $p > 0.1$, suggest non-significance in our analysis. Therefore, H2 and H3 are not supported by the findings of this study.

To ensure more robust estimation results, the data includes bootstrapped confidence intervals and standard errors of the mediation effect model using PROCESS software

(Table III). The sampling was performed 50,000 times, with a confidence interval of 95%. The findings, as shown in Table 3, encompass the three models employed to assess the impact of GenAI on attitude, trust, and employee engagement, and their subsequent influence on employee performance among individuals who have utilized these technologies. These results suggest that factors like Attitude, Trust, Engagement, and perceptions of Usefulness generally increase the outcome variable in question when they increase. However, the benefits of GenAI on the outcome might be less pronounced as these factors increase.

- Insert Table III about here -

Discussion

This study investigates the influence of GenAI on employee performance within workplace contexts from a managerial perspective. This investigation highlights the critical role of key determinants such as employee engagement, trust in GenAI, and attitudes towards its adoption. The findings reveal significant correlations among all independent variables (attitude, trust, and employee engagement) and the dependent variable (employee performance), with positive coefficients evident. Of particular interest is the moderating impact of GenAI, demonstrating a statistically significant positive interaction with employee performance, especially among individuals with prior exposure to and perceived benefits from these technologies. These results indicate the nascent integration of AI in Spanish companies, thereby activating favourable changes in Spanish employees' perceptions of technological advancements. As employees gain familiarity with GenAI and recognise its potential to support their job tasks, their performance consequently improves.

The exploration of GenAI and its implications for organisational strategy and culture is still in its emerging stages (Loureiro *et al*., 2021). Further literature is needed to delve into methods for enhancing employee competencies to align with technological advancements, while also developing trust and engagement in the implementation of AI tools. Corporations are facing with the critical challenge of finding a delicate equilibrium between AI's potential to either replace or complement human labour. This underlines the urgency for organisational decision-makers to prioritize the adaptation of workplaces for AI integration, thereby catalyzing strategic upskilling initiatives and facilitating knowledge dissemination (Secinaro *et al*., 2023).

The study reports a significant enhancement in employee engagement and performance attributed to improved attitudes and trust towards GenAI. It enriches the literature on GenAI adoption in Spanish companies from a management perspective regarding workforce performance. Trust is identified as a crucial factor for successful AI integration. Our findings suggest that prior positive experiences with AI can bolster trust and enhance performance. This aligns with studies such as Kim *et al*. (2021), which highlight the importance of trust in AI's functionality, reliability, and data protection for successful workplace integration and innovation.

Employee attitudes towards AI, particularly fear and scepticism, significantly impact their engagement and performance. We propose that positive attitudes towards GenAI have a greater impact on performance among those familiar with these technologies. The results underscore the importance of addressing and mitigating negative perceptions to foster acceptance. Managers should promote positive attitudes to mitigate these concerns (Mokyr *et al.*, 2015). Notably, our findings indicate that while positive attitudes towards GenAI correlate with enhanced engagement and performance, there exists a weakening effect on the overall positive impact of GenAI adoption in the workplace. This suggests that GenAI is still in its early stages of adoption within these companies, necessitating additional time for managers to develop greater confidence in its efficacy.

Engaged employees who utilise GenAI put forth their best efforts into their tasks, thereby increasing productivity and effectiveness at work. Moreover, the benefits of employee engagement extend to future performance, with a positive correlation observed with task performance and a negative correlation with absenteeism (Neuber *et al.*, 2022). This is supported by Bal *et al.* (2013) and Lin (2010), who explore employee behaviours that contribute to organisational success, emphasising that engaged employees perform better.

Theoretical Contributions

This study enriches the literature on GenAI adoption in Spanish companies from a management perspective on workforce performance. It draws on the TRI model to explain how technological optimism affects AI adoption. Optimistic employees are more likely to embrace AI, viewing it as a tool that offers increased control, flexibility, and efficiency in their roles. This relates to the TRI model by Parasuraman (2020), which posits that people's propensity to embrace and use new technologies is influenced by their technological optimism, suggesting a more proactive and accepting approach to AI technologies.

The application of the Stimulus-Organism-Response (S-O-R) framework helped analyse how GenAI acts as a stimulus affecting the emotional and cognitive responses (Organism) of employees, which in turn influence their behaviours (Response) towards AI integration. The TRI model complemented this by assessing readiness and optimism towards technology use. The S-O-R framework, from Mehrabian and Russell (1974), has been used to understand consumer behaviour in management contexts, providing a framework to assess how GenAI influences employee behaviour through environmental stimuli. Our research framework, based on the SOR model, helps dissect how external technological changes impact employee behaviour and organisational dynamics. It indicates that the readiness of organisations to adopt GenAI significantly influences its successful integration. Our study reveals that organisations need to develop strategies that align GenAI adoption with their operational and strategic goals, ensuring that employees are prepared for and supportive of the technological changes. In this context, managers play a crucial role in fostering support for the introduction of these new technologies.

Managerial implications

Companies today should prioritise understanding the role of GenAI within the workplace, as its integration could significantly enhance the efficiency of daily tasks when employees actively engage with AI technologies. GenAI holds the potential to assist employees in various activities, including composing emails, data analysis, and accessing up-to-date information to resolve intricate issues, thereby humanising the work experience. It is imperative for companies to address the concerns employees may have regarding the adoption of advanced technologies like GenAI in their respective departments and allocate resources towards training programmes aimed at equipping employees with the necessary skills to proficiently utilise AI tools in their work. Furthermore, the adoption of such technology may influence employee trust in its usage within workspaces, thus necessitating the establishment of clear regulations governing the utilisation of GenAI tools and platforms. This ensures that employees feel at ease and possess a sense of trust when incorporating such high-tech solutions into their daily work routines. The assimilation of new technologies typically requires an initial period for employee engagement, prompting companies to establish regular training programmes to expedite this acclimation process. These initiatives serve to enhance employee engagement by illustrating the practical utility of such technologies in efficiently achieving task objectives, thereby promoting heightened levels of performance.

Recommendations for Further research

While the sample size collected and used for this research provides sufficient statistical power, there remains potential for augmenting the study's breadth. Enlarging the sample to encompass a diverse array of professional roles across multiple organisations would furnish insights into both managerial viewpoints and employee sentiments concerning the adoption of GenAI in the workplace. Furthermore, this study has focused solely on British companies. Undertaking cross-country analyses would afford a more comprehensive understanding and facilitate comparative investigations in subsequent research contexts for future studies.

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