Journal of Innovation & Knowledge 11 (2026) 100844

Contents lists available at ScienceDirect

Journal of Innovation & Knowledge

journal homepage: www.elsevier.com/locate/jik

Generative AI and employee well-being: Exploring the emotional, social, and cognitive impacts of adoption

Serena Filippelli [a], Irina Alina Popescu [b], Saverino Verteramo [c,*], Mario Tani [d], Vincenzo Corvello [e]

[a] Department of Engineering for Industrial Systems and Technologies, University of Parma, Parma, Italy
[b] Department of International Business and Economics, Bucharest University of Economic Studies, Bucharest, Romania
[c] Department of Mechanical, Energy and Management Engineering, University of Calabria, Italy
[d] Department of Economics, Management, Institutions, Università of Naples Federico II, Naples, Italy
[e] Department of Engineering, University of Messina, Italy

A R T I C L E I N F O

JEL:
032

Keywords:
Generative artificial intelligence
Employee well-being
Emotional well-being
Social well-being
Cognitive well-being
Technology adoption

A B S T R A C T

Generative artificial intelligence (GenAI) is increasingly recognized as a transformative technology that is reshaping organizational processes, individual work practices, and workplace interactions. While its benefits for efficiency and productivity are widely acknowledged, its impact on employee well-being remains largely underexplored. This study investigates the relationship between GenAI adoption and three dimensions of employee well-being: emotional, social, and cognitive. Drawing on the job demands-resources (JD-R) model and social cognitive theory, we propose a conceptual framework in which the GenAI intensity of adoption mediates the relationship between employees' attitudes toward the technology and their well-being. By analyzing survey data from approximately 130 knowledge workers and analyzing it through partial least squares structural equation modeling (PLS-SEM), our findings reveal that a positive attitude toward GenAI significantly enhances its adoption, whereas a negative attitude does not necessarily prevent usage. Furthermore, the extent of GenAI adoption influences all three dimensions of well-being, with team cohesion acting as a mediating factor. These results contribute to the literature on workplace well-being and technology adoption by offering theoretical and managerial insights into the complex relationship between AI integration and employee experience.

Introduction

Generative artificial intelligence (GenAI) is widely considered a disruptive technology with the potential to revolutionize how businesses operate and how work is performed (Hoffmann et al., 2024; Arsenyan & Piepebrink, 2024), as well as how individuals interact, both within and beyond the workplace. This transformation has significant implications for personal and social well-being (Parteka et al., 2024). The projections for the development of AI, particularly GenAI, are striking. AI is expected to contribute $13 trillion annually to the global economy by 2030 (Bughin et al., 2018). Companies are making significant investments in AI (e.g., Smith, 2025), and governments are recognizing AI as a strategic opportunity (e.g., Jones et al., 2025).

GenAI is a specialized branch of AI that focuses on producing original content, such as text, images, and videos (Al-Khatib, 2023). In 2023, it attracted significant investment, amounting to approximately $100 billion (Aranca, 2024). By replicating and enhancing human creativity in fields that require extensive knowledge, GenAI has the potential to identify hidden patterns and foster innovation (Haefner et al., 2021). Its adoption in organizations has recently surged, driven by the emergence of intuitive conversational chatbots (e.g., ChatGPT), which are increasingly integrated across various industries, including education (Hashmi & Bal, 2024), tourism (Gursoy & Song, 2023), and professional domains, such as innovation management (Sedkaoui & Benaichouba, 2024).

GenAI is expected to transform the nature of work by substantially enhancing individual performance (Goldman Sachs, 2023). AI is already reshaping the roles of highly skilled professionals (Somers, 2024) and redefining leadership dynamics (Stackpole, 2024). GenAI fundamentally redefines professional roles. For instance, it is altering the responsibilities of project managers (Müller et al., 2024) and transforming the nature of software development (Hoffmann et al., 2024).

* Corresponding author.
E-mail address: saverino.verteramo@unical.it (S. Verteramo).

https://doi.org/10.1016/j.jik.2025.100844
Received 7 April 2025; Accepted 3 October 2025
Available online 19 October 2025
2444-569X/© 2025 The Authors. Published by Elsevier España, S.L.U. on behalf of Journal of Innovation & Knowledge. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Although the remarkable impact of these technologies on performance is widely acknowledged, a less intuitive but equally important effect remains underexplored: their impact on users' well-being (Zhang et al., 2024). Similar to other technologies, GenAI influences various aspects of work life that are closely related to employees' well-being (Parteka et al., 2024). The most immediate and apparent effect concerns emotional well-being. The adoption of new technologies is often associated with anxiety, stemming either from difficulties in mastering them or from fears of inadequate performance when using them in professional settings (Havrda & Klocek, 2023). A less obvious yet significant impact involves workplace relationships—both interpersonal and between humans and AI systems (Bailey et al., 2022). As the literature on communities of practice suggests, learning, knowledge exchange, and information sharing are deeply intertwined with social relationships (Wenger, 2000). More broadly, the work itself is embedded within a dense network of social interactions (Uzzi, 1997). If workers increasingly rely on GenAI for information and knowledge rather than consulting their colleagues, this shift inevitably affects workplace relationships (Hinds & von Krogh, 2024). The impact on well-being can be negative, reducing opportunities for socialization, but it could also be positive by empowering individuals who feel less confident in their expertise, thus improving their interactions with colleagues.

In the literature, well-being is often conceptualized as a multidimensional construct, including emotional (affective state), social (quality of interpersonal relationships), and cognitive (skill development and decision-making efficiency) well-being (O'Boyle et al., 2011; Xu & Wang, 2021). In an organizational context, these dimensions are essential for understanding the quality of work life, especially in the case of knowledge-based workers. Although GenAI can reduce the volume of repetitive work and support decision-making (Lam et al., 2002; Lozie et al., 2024), it can also negatively influence social relationships or increase stress, depending on how it is integrated.

Despite the growing integration of AI in workplaces, research on the impact of AI—particularly GenAI—on different dimensions of well-being remains scarce. To address this gap, this study aims to analyze the relationship between GenAI adoption levels and employee well-being. We develop and test a model in which the extent of GenAI adoption mediates the relationship between individuals' attitudes toward technology and their emotional, social, and cognitive well-being. To empirically validate this model, we conducted a survey of knowledge workers who actively use GenAI tools. Approximately 130 valid responses were collected and analyzed using partial least squares structural equation modeling (PLS-SEM) (Becker et al., 2023; Hair et al., 2019, 2021).

The theoretical contribution of this study lies in being among the first to examine the impact of GenAI on multiple dimensions of employee well-being, emphasizing its implications beyond task performance. Understanding how technologies affect various aspects of work life is essential to their effective integration and to mitigate unintended consequences. These findings hold relevance for scholars in the fields of organizational studies and technology, as well as for those researching workplace well-being. From a practical perspective, these findings offer valuable insights for managers responsible for innovation and technology adoption, as well as for HR professionals, by deepening our understanding of the complex relationships among technology, well-being, and work.

Theoretical background

Revisiting the concept of well-being in the age of AI

Well-being is a complex concept, analyzed from multiple theoretical perspectives, reflecting both the external conditions of individuals and their subjective perceptions of their own lives. Over time, the literature has outlined three major perspectives on the concept of well-being: subjective well-being, objective well-being, and the capabilities approach. Objective well-being refers to the normative assessment of living conditions, such as income, housing conditions, and access to economic opportunities (Gartaula et al., 2012; OECD, 2011; Popescu & Reis Mourao, 2025). In contrast, subjective well-being concerns individuals' perceptions of their own lives and includes dimensions such as general satisfaction, positive affect, and reduction of negative feelings (Diener et al., 2002; Frey & Stutzer, 2009; Veenhoven, 2012; OECD, 2020). A complementary perspective is that of capabilities, formulated by Nussbaum and Sen (1993), which understands well-being through the lens of the real freedoms and opportunities that individuals have to lead a valuable life. This approach pays particular attention to personal autonomy and social support and provides opportunities for personal development.

Based on these general foundations, the workplace literature has adapted the concept of well-being to the specifics of the workplace. Recent studies have proposed a multidimensional approach that highlights three main forms of employee well-being: emotional, social, and cognitive (O'Boyle et al., 2011; Xu & Wang, 2021). Emotional well-being reflects affective balance and the ability to cope with stress (Diener et al., 1999; Fisher, 2000), while social well-being is determined by the quality of relationships and team integration (Keyes, 2002; Chaudhuri & Ghosh, 2012). The cognitive component refers to the management of complex tasks, development of skills, and perception of one's own performance (Fisher, 2000).

In this context, the integration of GenAI-based technologies brings new challenges and opportunities for understanding employee well-being. GenAI can reduce cognitive load, automate repetitive tasks, and support learning and decision-making processes, thus contributing to emotional balance and professional development (Lam et al., 2002; Lozie et al., 2024; Kettlewell et al., 2020). Recent research has also highlighted the potential of language models and social robots to support mental health through virtual counseling and stress management (Revell, 2024). At the same time, the study by Shahzad et al. (2025) showed that the use of GenAI can have positive effects on psychological well-being, but these vary depending on the social context and the mode of use, highlighting the role of collaborative interaction as a moderating factor.

The relevance of GenAI in the work context is supported by the systematic analysis carried out by Al Naqbi et al. (2024), which highlights how the integration of these technologies affects employee productivity in various professional fields, such as health, education, business, engineering, and public administration. Al Naqbi et al. (2024) identified several factors that may limit the effectiveness of GenAI implementation, such as the lack of adequate staff training, difficulties in technological integration, issues related to information security, biases in data processing, and concerns about ethics and confidentiality. These aspects are directly related to the psychosocial conditions of work and can influence employees' perceptions of control, fairness, and professional stability. Therefore, GenAI's potential to contribute to employee well-being is conditioned by how these challenges are managed at the organizational and systemic levels.

In this context, where GenAI is increasingly present in professional dynamics and raises issues related to equity, security, and autonomy, a deeper reflection on the nature of this technology is also emerging. A recent philosophical perspective (Goldstein & Kirk-Giannini, 2025) suggests that some advanced intelligent agents, such as language models, could manifest their own forms of well-being. Although the hypothesis is controversial, it invites us to rethink the relationship between humans and AI, not only in functional terms but also as part of a moral and conceptual transformation in how we define well-being in the age of technology.

Attitude toward generative AI and its use

Employee attitudes toward GenAI are complex and multidimensional. The literature highlights that employee attitudes and perceptions play a key role in determining the success or failure of integrating AI into work and business processes (Köhler & Hartig, 2024; Huang & Gursoy, 2024). These attitudes are shaped by individual, organizational, and contextual factors that have a direct impact on the adoption and use of technology in the workplace (Bankins et al., 2024). On the one hand, employees may perceive AI as an opportunity to improve their work and efficiency; on the other hand, they may develop concerns about the replacement of human roles, the risk of automation, and the loss of control over their own careers (Lingmont & Alexiou, 2020; Suseno et al., 2022; Innocenti & Golin, 2022; Brougham & Haar, 2018). Thus, attitudes toward AI can influence the level of organizational commitment, work involvement, perception of job security, and, ultimately, the professional well-being of employees (Arias-Pérez & Vélez-Jaramillo, 2022; Suseno et al., 2022). Recent studies have also highlighted the existence of mixed attitudes, in which employees recognize both the benefits and potential risks of AI (Koo et al., 2021), which is consistent with the integrated acceptance/avoidance model proposed by Cao et al. (2021). This ambivalence is strongly influenced by the perception of usefulness, trust, ease of use, and support provided for training and adaptation (Chatterjee, Chaudhuri et al., 2021, S., 2021; Baabdullah et al., 2021).

Positive employee attitudes toward GenAI are generally associated with the perception that this technology can help improve work efficiency, automate repetitive tasks, and achieve faster and more accurate results (Sallam et al., 2024). Studies have shown that when employees perceive AI as easy to use and compatible with current activities, and the organization provides support in developing the necessary skills, their willingness to adopt it increases significantly (Chatterjee, Rana et al., 2021; Baabdullah et al., 2021). Additionally, according to the integrated model proposed by Cao et al. (2021), employees are more likely to accept AI when they believe that it contributes to achieving their goals and facilitates their work. Individuals with a high internal locus of control or who perceive AI as a challenging stressor rather than an obstacle are more motivated to adapt, retrain, and integrate AI into their daily work, increasing engagement and performance (Innocenti & Golin, 2022; Ding, 2021).

In contrast, negative attitudes toward GenAI are often fueled by fears that technology will completely replace certain jobs, reduce career opportunities, or make current skills obsolete (Lingmont & Alexiou, 2020; Innocenti & Golin, 2022; Suseno et al., 2022). Employees who perceive AI as a threat are more likely to experience job insecurity, anxiety, decreased work engagement, and reduced organizational commitment (Brougham & Haar, 2018; Arias-Pérez & Vélez-Jaramillo, 2022). These perceptions generate increased resistance to emerging technologies and active avoidance of AI, regardless of its potential benefits (Suseno et al., 2022; Tong et al., 2021). Furthermore, employees with low levels of autonomy in the organization or those in the early stages of their careers tend to perceive AI with more skepticism and fear, which reduces their ability to trust their own resources and adapt (Leonard & Tyers, 2021). In light of these considerations, it is hypothesized that:

H1a. A positive attitude toward GenAI positively influences its use by employees.

H1b. A negative attitude toward GenAI negatively influences its use by employees.

Use of generative AI and well-being

The concept of subjective well-being in the workplace refers to the subjective perception of the quality of one's work experience and the psychological state at work. Over the last few decades, a large number of studies (e.g. Lacković, 2019; Smaliukiene & Bekesiene, 2020) have shown that job characteristics can have a significant impact on employee subjective well-being by influencing aspects such as job stress, burnout, and job participation. The job demands-resources (JD-R) model (Demerouti et al., 2001) is one of the main theoretical references for understanding work-related well-being. This suggests that well-being is influenced by the balance between job demands (e.g., high pressure, emotional demands, and role ambiguities) and job resources (e.g., social support, autonomy, and performance feedback). While excessive demands may lead to stress and burnout, resources enhance motivational processes that promote commitment, learning, and organizational commitment (Bakker & Demerouti, 2007).

From this perspective, Smaliukiene and Bekesiene (2020) proposed a multidimensional view of subjective well-being, articulated in physical, cognitive, and socioemotional experiences—three components that together determine the quality of working life. Physical experiences refer to the influence of the physical environment on work well-being, including factors such as the quality of workspaces, ergonomics, and comfort. Although physical experiences have an impact on general well-being, their weight is less relevant for knowledge workers who work in contexts where the quality of their professional experience depends more on nonphysical dimensions, such as information management, organizational support, and interpersonal relationships. In this category of workers, interaction with technology and the quality of cognitive and emotional processes play a more decisive role than the physical environment. Cognitive experiences concern the perception of one's own performance, transparency in evaluation processes, and fairness in professional development opportunities (Fisher, 2000). These experiences are closely related to cognitive well-being (i.e., the ability to manage cognitive load, make effective decisions, and develop skills without incurring excessive mental fatigue). In parallel, socioemotional experiences represent the more complex dimension of occupational well-being and include the quality of relationships with colleagues and superiors, emotional support, and a sense of belonging to the professional context (Chaudhuri & Ghosh, 2012). Two distinct but interconnected dimensions emerge from these experiences: social well-being, which reflects the quality of interactions and the level of integration in the team (Keyes, 2002), and emotional well-being, which concerns emotional stability and the ability to manage stress and negative emotions (Diener et al., 1999).

The integration of GenAI in organizational contexts is redefining the dynamics of work (Bankins et al., 2024), directly affecting the three forms of well-being described above. Regarding *social well-being*, Guan et al. (2022, p. 1) stated that "artificial intelligence technology can enhance social well-being," a view supported by Köhler and Hartig (2024), who highlighted that AI contributes to improving workplace interactions by facilitating information exchange, optimizing communication, and reducing linguistic or cognitive barriers between workers. Tools such as ChatGPT enable smoother and more efficient communication, contributing to the creation of a more cohesive and collaborative working environment. Johnson et al. (2023) showed that preventing cumbersome administrative processes significantly contributes to reducing individual stress, which has a direct effect on well-being. Automating repetitive tasks, reducing human errors, and providing transparent and personalized decision support allow employees to focus on value-added activities and reduce the pressure associated with uncertainty and overload. Furthermore, McDonald (2024) argued that GenAI can support social well-being by facilitating communication, mutual care, and self-expression, in line with the principles of the ethics of care, provided the technology is designed to support relationships and inclusion, not replace them. In the same vein, Sison et al. (2024) emphasized that GenAI contributes to social well-being when implemented ethically, with the aim of reducing cognitive effort, stimulating creativity, and ensuring a safe and equitable framework for human interaction.

Emotional well-being is determined by the quality of interpersonal relationships and the ability to experience positive emotions in a professional context (Lacković, 2019; Smaliukiene & Bekesiene, 2020). However, the concept of emotional well-being goes beyond the simple absence of negative emotions and includes the ability to develop resilience and the adoption of coping strategies that help workers manage daily challenges in a constructive manner (Fisher, 2000). Recent literature has shown that GenAI can reduce work stress by automating repetitive tasks and reducing mental workloads, allowing employees to focus on higher value-added activities (Lozie et al., 2024). This promotes better emotional balance, reduces anxiety and burnout, and increases job engagement (Kettlewell et al., 2020; Diener et al., 1999). Furthermore, Almufarreh (2024) showed that emotional well-being is the most important factor in user satisfaction with educational AI tools, even exceeding content quality and perceived usefulness. Orji et al. (2024) demonstrated that the use of GenAI improves well-being and connectivity and reduces stress, providing users with a sense of companionship. Papadopoulos et al. (2022) provided significant evidence that culturally competent social robots can improve users' emotional well-being.

Finally, concerning *cognitive well-being*, GenAI can support workers by improving information management, optimizing decision-making processes, and facilitating skills development (Smaliukiene & Bekesiene, 2020). The ability to quickly access complex data, generate summaries, and receive suggestions in real time can reduce cognitive overload and increase work effectiveness (Lam et al., 2002). According to Bandura's (1986) social cognitive theory, individuals are not passive in their work environment but actively seek to improve their skills and manage the resources available to them. In this sense, if AI is used as support and not as a substitute for human thinking, it can actually improve cognitive well-being. Therefore, the following hypotheses are formulated:

H2a. Employees' use of GenAI positively influences their social well-being.

H2b. Employees' use of GenAI positively influences their emotional well-being.

H2c. Employees' use of GenAI positively influences their cognitive well-being.

Mediating role of team cohesion between GenAI use and well-being

The use of GenAI in work contexts is profoundly transforming the dynamics of collaboration, directly affecting team cohesion. Cohesion is defined as the tendency of a group to stick together and collaborate to achieve common goals (Carron, 1982), and it is a key element in the effective functioning of work teams. Tekleab et al. (2009) pointed out that cohesive teams foster a more collaborative working environment, which improves job satisfaction, perceptions of performance, and the sustainability of group dynamics. The use of GenAI can facilitate team cohesion by improving collaboration and knowledge sharing. A crucial aspect of team cohesion is the quality of communication among members (Troth et al., 2012). The use of GenAI optimizes information flows, reduces ambiguities, and improves data accessibility, contributing to greater clarity in work interactions. This leads to the strengthening of mutual trust and psychological safety, which are fundamental elements of a cohesive team (Puranam, 2021). Furthermore, GenAI-supported teams show superior performance compared to those that rely solely on human collaboration due to the ability of AI to optimize information management and task coordination (Li et al., 2024). Thus, the following hypothesis can be formulated:

H3a. Employees' use of GenAI positively influences team cohesion.

In addition to fostering cohesion, GenAI influences workers' subjective well-being through its mediating role in team cohesion. Cohesion acts as a key factor in linking the use of GenAI to the three main dimensions of work well-being: social, emotional, and cognitive well-being.

Regarding social well-being, team cohesion is essential to creating a climate of support and belonging. A work environment characterized by strong relationships and effective interactions contributes to an improved sense of social integration and reduces employee isolation (Beullens et al., 2014; Vanhove & Herian, 2015). Since GenAI improves communication and collaboration, its positive influence on social well-being is amplified by team cohesion.

Emotional well-being benefits from a cohesive team, as the presence of supportive interpersonal relationships helps employees manage stress and negative emotions. A harmonious and collaborative work environment reduces psychological pressure and promotes greater emotional stability (Chaudhuri & Ghosh, 2012). GenAI, by automating repetitive tasks and reducing workload, can contribute to decreasing work anxiety, but it is the cohesion of the team that determines how much these effects translate into an actual improvement in emotional well-being.

Finally, cognitive well-being is influenced by team cohesion, as a collaborative environment fosters knowledge sharing, collective problem solving, and reduced cognitive fatigue (Smaliukiene & Bekesiene, 2020). The use of GenAI provides support for decision-making and information processing, but it is the ability of a cohesive team to effectively integrate these technologies that determines their real impact on managing cognitive load and developing workers' skills.

H3b1. Team cohesion mediates the relationship between the use of GenAI and social well-being.

H3b2. Team cohesion mediates the relationship between the use of GenAI and emotional well-being.

H3b3. Team cohesion mediates the relationship between the use of GenAI and cognitive well-being.

Research methods

Sample, measures, and data collection

To test the hypotheses developed in our conceptual model, we collected data from 158 knowledge workers working in Italy, but we had to delete 29 answers because they were incomplete, leaving us with 129 answers in the final sample. To design the questionnaire, we adopted several multi-item scales previously used in the literature. As shown in Table 1, we used a three-item scale—such as "I spend a lot of time using Generative AI tools"—to measure the use of GenAI (variable GAI) (Al-Emran et al., 2024), while team cohesion (Tekleab et al., 2009) was measured with a five-item scale—such as "The members of this organization help each other when working on a task" or "We all take responsibility for any loss or poor performance of our team." To measure well-being, we used three constructs to differentiate among emotional well-being (EW) (Frydenberg et al., 2009), social well-being (SW) (adapted for the workplace context from European Social Survey, 2012), and cognitive well-being (CW) (adapted from Smaliukiene and Bekesiene (2020) and Tennant et al. (2007)), measuring each of them with 6 items adapted from literature to the workplace context, for example, "How much of the time did you feel relaxed and free of tension while at work?" or "I rarely experience mental fatigue or cognitive overload in my work." Eventually, for the positive attitude (Köhler & Hartig, 2024) and the negative attitude (Köhler & Hartig, 2024) toward GenAI, we have used 4 items each, for example, "Generative AI is among the most important inventions of the 21st century" or "Generative AI contributes to the spread of misinformation." The entire set of scales used in our survey is reported in Table 1.

We collected data in January 2025. We collected 129 complete answers composed mostly of men (57.36 %), and most of the respondents were in the 35–44 age bracket (43.41 %), closely followed by the 25–34 age bracket (40.31 %). They were working in some part of a hybrid setting; for example, they worked partially remotely and partially in the office. The main statistics of the participants are reported in Table 2.

Table 1
Questionnaire scales and related sources.

Variable	Code	Items	Assessment	Source:
Generative AI Use (GAI)	GAI1	I use Generative AI tools frequently.	Strongly disagree, disagree, neutral, agree, strongly agree	Al-Emran et al. (2024)
	GAI2	I spend a lot of time using Generative AI tools.		
	GAI3	I exert myself to use Generative AI tools.		
Team Cohesion (TC)	TC1	Our organization members communicate freely about each of our personal responsibilities in getting a task done.	Strongly disagree, disagree, neutral, agree, strongly agree	Tekleab et al., (2009)
	TC2	We all take responsibility for any loss or poor performance by our team.		
	TC3	The members of this organization help each other when working on a task.		
	TC4	The members of this organization get along well together.		
	TC5	The members of this organization stick together.		
Emotional Well-being (EW)	EW1	In the past month…. How much of the time have you felt that your future in this organization looks hopeful and promising?	Never, rarely, sometimes, often, always	Adapted for workplace context from Frydenberg et al., (2009)
	EW2	How much of the time has your work been full of tasks and responsibilities that are interesting to you?		
	EW3	How much of the time did you feel relaxed and free of tension while at work?		
	EW4	How much of the time have you felt valued and appreciated by your colleagues and/or supervisors?		
	EW5	How much of the time have you felt happy and satisfied with your work experience?		
	EW6	How much of the time have you felt that you are a valuable and competent employee, as good as your colleagues in similar roles?		
Social Well-being (SW)	SW1	I feel lonely or isolated at my workplace (Loneliness).	Strongly disagree, disagree, neutral, agree, strongly agree	Adapted for workplace context from European Social Survey (2012)
	SW2	I receive help and support from colleagues and supervisors when needed (Help).		
	SW3	I feel close to my colleagues at workplace (Sense of belonging).		
	SW4	People at work try to take advantage of others (Perceived exploitation).		
	SW5	Most people at work can be trusted (Trust).		
	SW6	I can openly discuss work-related concerns with colleagues (Openness).		
Cognitive Well-being (CW)	CW1	I feel mentally sharp and capable of solving complex problems.	Strongly disagree, disagree, neutral, agree, strongly agree	Adapted from Smaliukiene & Bekesiene (2020)
	CW2	I feel that my cognitive abilities (such as reasoning, memory, and problem-solving) are functioning at a high level.		
	CW3	I rarely experience mental fatigue or cognitive overload in my work.		
	CW4	I have been thinking clearly.		Tennant et al. (2007)
	CW5	I am able to analyze and solve work-related problems effectively.		
	CW6	I feel confident in my ability to process information and make decisions at work.		
Positive Attitude toward Gen AI (POS_ATT)	AP1	Generative AI is among the most important inventions of the 21st century.	Strongly disagree, disagree, neutral, agree, strongly agree	Köhler and Hartig (2024)
	AP2	Generative AI is easy to use and accessible to a wide audience.		
	AP3	Generative AI is a reliable source of information.		
	AP4	Generative AI helps improve productivity and efficiency.		
Negative Attitude toward Gen AI (NEG_ATT)	AN1	Generative AI reproduces stereotypes and biases.	Strongly disagree, disagree, neutral, agree, strongly agree	Köhler and Hartig (2024)
	AN2	Generative AI contributes to the spread of misinformation.		
	AN3	Generative AI raises concerns about copyright and intellectual property rights.		
	AN4	Generative AI consumes too much energy, negatively impacting the environment.		

Data analysis

To test the hypotheses in our conceptual model, we adopted a PLS-SEM (partial least squares approach to structural equation modelling) (Hair et al., 2011; 2021), implemented using the seminr (2.3.4) package in R-Cran (4.4.1). According to some authors (Hair et al., 2021), the PLS approach, that is, a composite-based SEM method (Hwang et al., 2020), assumes that concepts may be measured as composite variables that can be considered valid proxies of the concepts (Hair et al., 2019), and it has proven to be particularly effective when studying small sample sizes and complex models (Cassel et al., 1999; Hair et al., 2019). Furthermore, this approach does not rely on the distributional assumption of the variables (Hair et al., 2017a, 2017b), and it is particularly suited for models adopting ordinal scales, such as in our case (Sarstedt & Mooi, 2019). Furthermore, the PLS-SEM approach has been shown to provide results that are at least as good as those of covariance-based SEM when the sample size is small and there are only a few indicators for each latent variable (Hair et al., 2019). This approach has been used in different fields related to our study, such as studies on employee well-being (e.g., Muhammad et al., 2022), in the adoption of GenAI (e.g., Cimino et al., 2024; Popescu & Stam, 2025), and in its effect on specific aspects of employee performance, such as their creativity (Zhang et al., 2024). This approach is usually applied by studies (Hair et al., 2021) using a two-step approach: (1) the quality of the outer (measurement) model and (2) the assessment of the inner (structural) model's predictive power.

Results

Measurement model

In the first step, we must evaluate the quality of the indicators and how we measured them. In particular, we must verify the reliability of the indicator, which should be greater than 0.7 (Hair et al., 2021). According to Hair et al. (2021), if the values are lower than 0.7 but higher than 0.4, they should be deleted, and the model should be retested.

Table 2
Descriptive statistics.

Gender	*Count*	%
Female	55	42.64 %
Male	74	57.36 %
Age	*Count*	%
Under 25	4	3.10 %
25–34	52	40.31 %
35–44	56	43.41 %
45–54	17	13.18 %
Over 54	0	0.00 %
Work Mode	*Count*	%
Fully in-office	34	26.36 %
Fully remote	14	10.85 %
Hybrid (part remote, part in-office)	81	62.79 %

Using this procedure led us to the removal of 6 items (CW3, EW3, GAI3, POS_ATT3, NEG_ATT1, and SW4).

The second element to consider is the internal consistency reliability, which is usually assessed using Jöreskog's (1971) composite reliability rhoC, Cronbach's alpha, and the reliability coefficient rhoA (Dijkstra, 2014). Our model surpassed the suggested threshold of 0.7 for each construct. To evaluate convergent validity, we used the average variance extracted (AVE) for all indicators, checking that it was greater than 0.5 (Hair et al., 2021). The data for these tests are reported, with R^2 of the model, in Table 3.

Finally, to evaluate the discriminant validity of our model, we have used both the Fornell–Larcker criterion and the HTMT (Henseler et al., 2015), as reported in Table 4. As a criterion, for the Fornell–Larcker criterion, the square root of AVE for a given constrict should be higher than the constructs' correlation with the other constructs, while the HTMT values must be <0.85 for constructs that are conceptually different and 0.90 for those that are conceptually very similar.

Structural model

We checked the quality of the model using R^2, which is reported in Table 3. Some scholars have defined rough measures to identify substantial, moderate, and weak predictive power. The most frequently used were defined by Hair et al. (2011) as 0.75, 0.5, and 0.25, respectively. The study of R^2 shows that, in general, our model has a "moderate" prediction power for social well-being (0.326), while only a weak prediction power for emotional and cognitive well-being (0.194 and 0.184, respectively).

After this test of the structural model, we looked at the predictive power of the model using the PLSpredict approach (Shmueli et al., 2019). This approach is considered more conservative than the CVPAT approach (Sharma et al., 2023), as its results are calculated factoring in the effect of all the early antecedents and not only of the direct antecedents (Sarstedt et al., 2019). Using this approach, we found that the PLS out-of-sample error is lower than the naïve LM out-of-sample error by 11 times on 21 for the RMSE and by 10 times on 21 for the MAE; the model has medium predictive power (Shmueli et al., 2019).

After these two tests, we used a bootstrap procedure (5000 resamples according to Hair et al., 2021) to test our hypotheses. The results of these tests are reported in Fig. 1 and Table 5.

As shown in all the paths, we found support for most of the paths in our conceptual framework. Specifically, we did not find support for the hypothesis NEG_ATT on GAI or for the direct effect of GAI on CW.

Discussion

In this research, we investigated how adopting GenAI may influence employee well-being. We adopted a three-dimensional vision of well-being that builds on the model developed by Smaliukiene and Bekesiene (2020). We applied the model to knowledge workers, removing the physical dimension, as it may be less relevant in this context, and focused on the cognitive dimension.

Our results show that positive and negative attitudes toward AI have different effects on the extent of adoption. This confirms the results of previous studies adopting a behavioral perspective to investigate factors supporting or hindering a given behavior (see, e.g., Claudy et al., 2013; Tani et al., 2022).

In particular, our results confirm the findings of some previous studies (Bankins et al., 2024; Sallam et al., 2024), which state that an employee's positive attitude toward AI is a relevant factor in helping companies implement these new technologies. At the same time, we did not find support for the idea that the usage of GenAI is significantly limited by a negative attitude, which is in contrast with several previous studies (e.g. Arias-Pérez & Vélez-Jaramillo, 2022; Suseno et al., 2023). These results might be explained by considering that the level of adoption is often an organizational decision and is not based on the employee perception of AI services. Indeed, the low R^2 we found for GAI hints at the existence of several other predictors of this behavior.

At the same time, we found that GAI was able to influence both social well-being and emotional well-being, thus confirming the previous results by Köhler and Hartig (2024). However, it does not have a significant effect on cognitive well-being, hinting that while these tools may improve information management (Smaliukiene & Bekesiene, 2020) and may reduce cognitive fatigue from repetitive tasks (Lam et al., 2002), they may drive behaviors that reduce employee well-being. This finding is reinforced by evidence that GAI's effect on cognitive well-being is fully mediated by team cohesion, highlighting the role of the work context, as shown by Beullens et al. (2014). Similarly, we found that the effect of team cohesion on social and emotional well-being was also positive.

Theoretical implications

Our results support the idea that for knowledge workers, it is relevant to study social well-being separately from cognitive well-being, at least when considering the effects of new technologies. We found that adopting GenAI services in the workplace has a different impact on these two subdimensions, with a positive influence on social well-being and an insignificant one on cognitive well-being. This is partially due to the characteristics of these technologies that may help to improve the working climate (Köhler & Hartig, 2024), even if this may lead employees to feel less empowered in their cognitive work, reducing cognitive well-being (Koeszegi, 2024) and increasing the fear of losing control of their work (Bankins et al., 2024).

At the same time, our results highlight that team cohesion is a relevant factor in making organizations get the most out of GenAI. Team cohesion fully mediates the relationship between GAI and cognitive well-being, further supporting the relevance of the working climate to the satisfaction that knowledge workers may get from their work, even when it is enhanced by GenAI. The results suggest that a better climate, which supports the widespread adoption of GenAI services in the organization, helps employees to focus on the most satisfying and stimulating tasks (Lam et al., 2002).

Lastly, we found that GAI is one of the drivers of team cohesion, further supporting the idea that these technologies help improve collaboration and knowledge sharing in the workplace, in line with previous results by Troth et al. (2012). At the same time, our results show that while these relationships have moderate-to-good predictive power, the relatively low R^2 for the well-being constructs hints that there are other drivers at play.

Managerial implications

Our study has several results that might be relevant to practitioners. In particular, the first remark is that GenAI may indeed improve the well-being of employees, probably as a way to alleviate the burden of the most tedious and repetitive tasks or as a tool to support them in the most

Table 3
Measurement model test, reliabilities, and convergent validity.

Construct	Item	Outer Loading	alpha	rhoC	rhoA	AVE	R^2
GAI	GAI1	0.949	0.818	0.914	0.911	0.841	0.145
	GAI2	0.884					
TC	TC1	0.749	0.874	0.909	0.887	0.669	0.033
	TC2	0.718					
	TC3	0.902					
	TC4	0.869					
	TC5	0.837					
POS_ATT	POS_ATT1	0.821	0.729	0.846	0.756	0.648	–
	POS_ATT2	0.719					
	POS_ATT4	0.869					
NEG_ATT	NEG_ATT2	0.734	0.752	0.763	0.754	0.522	–
	NEG_ATT3	0.771					
	NEG_ATT4	0.834					
SW	SW1	0.747	0.793	0.866	0.798	0.618	0.326
	SW2	0.813					
	SW3	0.833					
	SW5	0.748					
EW	EW1	0.768	0.899	0.925	0.902	0.712	0.194
	EW2	0.792					
	EW4	0.829					
	EW5	0.873					
	EW6	0.816					
CW	CW1	0.841	0.874	0.909	0.879	0.666	0.184
	CW2	0.799					
	CW4	0.829					
	CW5	0.858					
	CW6	0.890					

Notes: GAI - Generative AI Use; TC - Team Cohesion; POS_ATT- Positive Attitude toward Gen AI; NEG_ATT - Negative Attitude toward Gen AI; SW - Social well-being; EW - Emotional well-being; CW - Cognitive well-being.

Table 4
Measurement model tests of discriminant validity.

	GAI	TC	POS_ATT	NEG_ATT	SW	EW	CW
GAI	0.917	*0.207*	*0.358*	*0.057*	*0.343*	*0.27*	*0.243*
TC	0.238	0.818	*0.47*	*0.244*	*0.518*	*0.383*	*0.41*
POS_ATT	0.447	0.581	0.805	*0.284*	*0.327*	*0.213*	*0.39*
NEG_ATT	0.138	0.394	0.418	0.725	*0.114*	*0.168*	*0.112*
SW	0.408	0.614	0.422	0.138	0.786	*0.611*	*0.571*
EW	0.309	0.43	0.259	0.206	0.73	0.816	*0.589*
CW	0.274	0.452	0.484	0.215	0.675	0.668	0.844

Notes:.
Fornell–Larcker Criterion – Upper Triangle: Diagonal in Bold: Square Root of AVE; Upper Triangle in Italic: Constructs Correlation. HTMT: Lower Triangle.
GAI - Generative AI Use; TC - Team Cohesion; POS_ATT- Positive Attitude toward Gen AI; NEG_ATT - Negative Attitude toward Gen AI; SW - Social well-being; EW - Emotional well-being; CW - Cognitive well-being.

complex ones.

At the same time, managers should consider that before implementing these services, they should work on improving team cohesion and promoting an environment that is supportive of these technologies. This is necessary to create a context that supports the social and emotional dimensions of employee well-being but also a factor to counter the potentially negative effects that adopting GenAI may have on cognitive well-being. Managers should make it clear to employees that GenAI services are not a substitute for knowledge work but must be seen as a way to express themselves in a more meaningful way without getting bogged down in day-to-day operations.

Another interesting result is the different effects that positive and negative attitudes toward AI may have on the adoption of these technologies. On the one hand, managers must factor in the amplifying effect that a positive employee attitude toward GenAI can have on the effective deployment of these services in the workplace. Consequently, managers should try to develop programs to create a positive attitude, explaining, since the first phases of deployment, the potential advantages that knowledge workers will have from adopting GenAI in their work. However, managers should not be too concerned that a negative attitude of their employees toward GenAI will lead to failure in its adoption.

Conclusion

This study provides theoretical and empirical insights into the impact of GenAI on employee well-being, specifically across emotional, social, and cognitive dimensions. Our findings demonstrate that a positive attitude toward GenAI significantly enhances its adoption, whereas a negative attitude does not necessarily prevent its usage. The extent of GenAI adoption directly influences both emotional and social well-being, while cognitive well-being is indirectly influenced by the mediating effect of team cohesion. These results highlight the complex relationships among technology adoption, workplace dynamics, and employee well-being.

From a theoretical point of view, this study contributes to understanding the role of GenAI in the workplace. The results suggest that while GenAI can foster social and emotional well-being by improving collaboration and reducing task-related stress, its impact on cognitive well-being depends on organizational and team-level factors. The role of team cohesion as a mediator reinforces the idea that the successful integration of AI technologies requires supportive social environments.

For practitioners, our findings indicate that managers should not only focus on providing access to GenAI tools but also invest in fostering

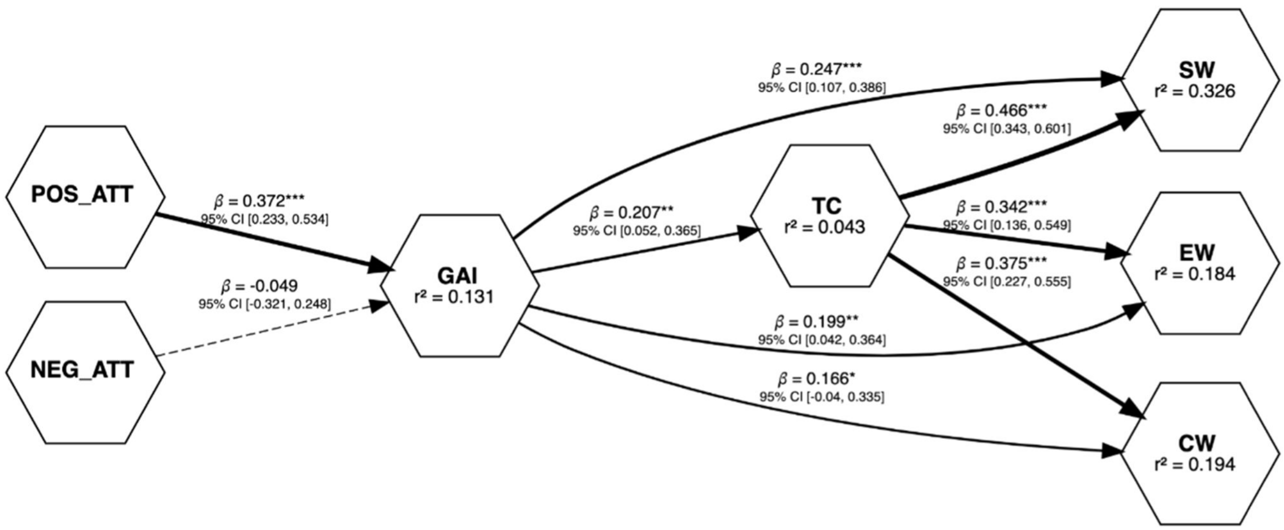

Fig. 1. Results of hypothesis testing. Note: GAI - Generative AI Use; TC - Team Cohesion; POS_ATT- Positive Attitude toward Gen AI; NEG_ATT - Negative Attitude toward Gen AI; SW - Social well-being; EW - Emotional well-being; CW - Cognitive well-being.

Table 5
Results of hypothesis testing.

Path	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5 % CI	97.5 % CI	SUPPORT
POS_ATT ≥ GAI	0.372	0.382	0.083	4.48	0.233	0.534	YES
NEG_ATT ≥ GAI	−0.049	−0.034	0.155	−0.316	−0.321	0.248	NO
GAI ≥ SW	0.247	0.245	0.076	3.243	0.107	0.386	YES
GAI ≥ EW	0.199	0.2	0.083	2.397	0.042	0.364	YES
GAI ≥ CW	0.166	0.16	0.1	1.66	−0.04	0.335	NO
GAI ≥ TC	0.207	0.218	0.08	2.597	0.052	0.365	YES
TC ≥ SW	0.466	0.481	0.066	7.045	0.343	0.601	YES
TC ≥ EW	0.342	0.357	0.106	3.218	0.136	0.549	YES
TC ≥ CW	0.375	0.39	0.087	4.304	0.227	0.555	YES

Note: GAI - Generative AI Use; TC - Team Cohesion; POS_ATT- Positive Attitude toward Gen AI; NEG_ATT - Negative Attitude toward Gen AI; SW - Social well-being; EW - Emotional well-being; CW - Cognitive well-being.

a collaborative work culture. Team cohesion plays a critical role in shaping how employees perceive and benefit from GenAI adoption, highlighting the need for organizations to create environments in which AI is seen as an enabler rather than a threat.

Despite its contributions, this study has several limitations that should be acknowledged. The study is based on a sample of knowledge workers, primarily from hybrid work settings. While this provides relevant insights into AI adoption in modern workplaces, the findings may not be generalizable to other types of workers (e.g., manual workers and service employees). This study relies on cross-sectional survey data, which limits the ability to establish causal relationships. Future longitudinal studies would help track changes in attitudes and well-being over time as AI adoption evolves. Employee well-being and AI adoption levels were measured through self-reported surveys, which may be subject to biases such as social desirability and response consistency effects. Organizational culture, industry norms, and job roles may influence how AI adoption impacts well-being. A broader range of industries and geographical contexts should be explored to improve external validity. Although team cohesion emerged as a key mediator, other potential factors, such as job autonomy, digital literacy, and AI training opportunities, were not directly examined but may also influence the AI–well-being relationship.

To address these limitations and expand on our findings, future research should consider the following directions:

- Longitudinal studies: Future studies should track employees over time to examine how AI adoption dynamically affects well-being.
- Experimental or mixed-methods approaches: Combining survey data with experimental interventions or qualitative insights (e.g., interviews and case studies) could provide a more nuanced understanding of how employees interact with AI tools.
- Exploration of additional moderators: Future research should investigate how factors such as job type, organizational culture, leadership support, and AI-related training programs moderate the relationship between GenAI adoption and well-being.

Furthermore, our study adopt a specific perspective—focusing on the effect of GenAI adoption on well-being. Future research could model this relationship differently. For example, GenAI adoption could be framed as a mediator or a moderator in the relationship between organizational factors (e.g., team cohesion, organization culture, and/or job autonomy) and the three dimensions of employee well-being.

By addressing these gaps, future research can provide deeper insights into the evolving role of AI in workplaces and inform strategies for optimizing both technological integration and employee well-being.

CRediT authorship contribution statement

Serena Filippelli: Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Irina Alina Popescu:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation, Conceptualization. **Saverino Verteramo:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mario Tani:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation. **Vincenzo Corvello:** Writing – original draft, Supervision, Conceptualization.

Acknowledgment / Funding

This work was supported by the project "Patti territoriali dell'alta formazione per le imprese - Industry 4.0 & Smart Manufacturing", funded under the Italian Prime Minister's Decree of 26 September 2023 (pursuant to Article 14-bis, paragraph 2, of Decree-Law No. 152/2021), CUP: H52C23000090001.).

References

Al Naqbi, H., Bahroun, Z., & Ahmed, V. (2024). Enhancing work productivity through generative artificial Intelligence: A comprehensive literature review. *Sustainability, 16*(3), 1166. https://doi.org/10.3390/su16031166
Al-Emran, M., AlQudah, A. A., Abbasi, G. A., Al-Sharafi, M. A., & Iranmanesh, M. (2024). Determinants of using AI-based chatbots for knowledge sharing: Evidence from PLS-SEM and fuzzy sets (fsQCA). *IEEE Transactions on Engineering Management, 71*, 4985–4999. https://doi.org/10.1109/TEM.2023.3237789
Al-Khatib, A. W. (2023). Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: A TOE framework. *Technology in Society, 75*, Article 102403. https://doi.org/10.1016/j.techsoc.2023.102403
Almufarreh, A. (2024). Determinants of students' satisfaction with ai tools in education: A PLS-SEM-ANN approach. *Sustainability, 16*(13), 5354. https://doi.org/10.3390/su16135354
Aranca (2024, September 1). Tracking the surge in generative AI investments. https://www.aranca.com/knowledge-library/articles/business-research/tracking-the-surge-in-generative-ai-investments.
Arias-Pérez, J., & Vélez-Jaramillo, J. (2022). Ignoring the three-way interaction of digital orientation, not-invented-here syndrome and employee's artificial intelligence awareness in digital innovation performance: A recipe for failure. *Technological Forecasting and Social Change, 174*, Article 121305. https://doi.org/10.1016/j.techfore.2021.121305
Arsenyan, J., & Piepenbrink, A. (2024). Artificial Intelligence Research in Management: A computational literature review. *IEEE Transactions on Engineering Management, 71*, 5088–5100. https://doi.org/10.1109/TEM.2022.3229821
Baabdullah, A. M., Alalwan, A. A., Slade, E. L., Raman, R., & Khatatneh, K. F. (2021). SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices. *Industrial Marketing Management, 98*, 255–270. https://doi.org/10.1016/j.indmarman.2021.09.003
Bailey, D. E., Faraj, S., Hinds, P. J., Leonardi, P. M., & von Krogh, G. (2022). We are all theorists of technology now: A relational perspective on emerging technology and organizing. *Organization Science, 33*(1), 1–18. https://doi.org/10.1287/orsc.2021.1562
Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of managerial psychology, 22*(3), 309–328. https://doi.org/10.1108/02683940710733115
Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.
Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior, 45*(2), 159–182. https://doi.org/10.1002/job.2735
Becker, J. M., Cheah, J. H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management, 35*(1), 321–346. https://doi.org/10.1108/IJCHM-04-2022-0474
Beullens, K., Matsuo, H., Loosveldt, G., & Vandenplas, C. (2014). *Quality report for the european social survey, round 6*. London: European Social Survey ERIC.
Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization, 24*(2), 239–257. https://doi.org/10.1017/jmo.2016.55
Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. *McKinsey Global Institute*. https://www.mckinsey.com/featured-insights/artificial-intelli-gence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy/.
Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation, 106*, Article 102312. https://doi.org/10.1016/j.technovation.2021.102312
Carron, A. V. (1982). Cohesiveness in sport groups: Interpretations and considerations. *Journal of Sport Psychology, 4*(2), 123–138. https://doi.org/10.1123/jsp.4.2.123
Cassel, C., Hackl, P., & Westlund, A. H. (1999). Robustness of partial least-squares method for estimating latent variable quality structures. *Journal of Applied Statistics, 26*(4), 435–446. https://doi.org/10.1080/02664769922322
Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A., & Ghosh, S. K. (2021a). Adoption of artificial intelligence-integrated CRM systems in agile organizations in India. *Technological Forecasting and Social Change, 168*, Article 120783. https://doi.org/10.1016/j.techfore.2021.120783
Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021b). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change, 170*, Article 120880. https://doi.org/10.1016/j.techfore.2021.120880
Chaudhuri, S., & Ghosh, R. (2012). Reverse mentoring: A social exchange tool for keeping the boomers engaged and millennials committed. *Human Resource Development Review, 11*(1), 55–76. https://doi.org/10.1177/1534484311417562
Cimino, A., Felicetti, A. M., Corvello, V., Ndou, V., & Longo, F. (2024). Generative artificial intelligence (AI) tools in innovation management: A study on the appropriation of ChatGPT by innovation managers. *Management Decision*. https://doi.org/10.1108/MD-10-2023-1968
Claudy, M. C., Peterson, M., & O'Driscoll, A. (2013). Understanding the attitude-behavior gap for renewable energy systems using behavioral reasoning theory. *Journal of Macromarketing, 33*(4), 273–287. https://doi.org/10.1177/0276146713481605
Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology, 86*(3), 499–512. https://doi.org/10.1037/0021-9010.86.3.499
Diener, E., Oishi, S., & Lucas, R.E. (.2002). Subjective well-being: The science of happiness and life satisfaction. In The oxford handbook of positive psychology. Oxford University Press.
Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective wellbeing: Three decades of progress. *Psychological Bulletin, 125*(2), 276–302. https://doi.org/10.1037/0033-2909.125.2.276
Dijkstra, T. K. (2014). PLS' Janus face–response to professor Rigdon's 'rethinking partial least squares modeling: In praise of simple methods. *Long Range Planning, 47*(3), 146–153. https://doi.org/10.1016/j.lrp.2014.02.004
Ding, L. (2021). Employees' challenge-hindrance appraisals toward STARA awareness and competitive productivity: A micro-level case. *International Journal of Contemporary Hospitality Management, 33*(9), 2950–2969. https://doi.org/10.1108/IJCHM-09-2020-1038
European Social Survey. (2012). *European social survey round 6 data (2012) questionnaire*. Norwegian Centre for Research Data (NSD). https://doi.org/10.21338/NSD-ESS6-2012
Fisher, C. D. (2000). Mood and emotions while working: Missing pieces of job satisfaction? *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, 21*(2), 185–202. https://doi.org/10.1002/(SICI)1099-1379(200003)21:2. <185::AID−JOB34>3.0.CO;2-M.
Frey, B. S., & Stutzer, A. (2009). *Should national happiness be maximized? happiness, economics and politics*. Edward Elgar Publishing.
Frydenberg, E., Care, E., Chan, E., & Freeman, E. (2009). Interrelationships between coping, school connectedness and wellbeing. *Australian Journal of Education, 53*(3), 261–276. https://doi.org/10.1177/000494410905300305
Gartaula, H. N., Visser, L., & Niehof, A. (2012). Socio-Cultural dispositions and wellbeing of the women left behind: A case of migrant households in Nepal. *Social Indicators Research, 108*(3), 401–420. https://doi.org/10.1007/s11205-011-9883-9
Goldman Sachs (2023, August 1). AI investment forecast to approach $200 billion globally by 2025. https://www.goldmansachs.com/insights/articles/ai-investment-forecast-to-approach-200-billion-globally-by-2025.
Goldstein, S., & Kirk-Giannini, C. D. (2025). AI wellbeing. *Asian Journal of Philosophy, 4*(1), 25. https://doi.org/10.1007/s44204-025-00246-2
Guan, H., Dong, L., & Zhao, A. (2022). Ethical risk factors and mechanisms in artificial intelligence decision making. *Behavioral Sciences, 12*(9), 343. https://doi.org/10.3390/bs12090343
Gursoy, D., Li, Y., & Song, H. (2023). ChatGPT and the hospitality and tourism industry: An overview of current trends and future research directions. *Journal of Hospitality Marketing Management, 32*(5), 579–592. https://doi.org/10.1080/19368623.2023.2211993
Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change, 162*, Article 120392. https://doi.org/10.1016/j.techfore.2020.120392
Hair, J. F., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017a). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems, 117*(3), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130
Hair, J. F., Matthews, L., Matthews, R., & Sarstedt, M. (2017b). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis, 1*(2), 107–123. https://doi.org/10.1504/IJMDA.2017.087624
Hair, F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019a). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202
Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019b). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing, 53*(4), 566–584. https://doi.org/10.1108/EJM-10-2018-0665
Hashmi, N., & Bal, A. S. (2024). Generative AI in higher education and beyond. *Business Horizon, 67*(5), 607–614. https://doi.org/10.1016/j.bushor.2024.05.005
Havrda, M., & Klocek, A. (2023). Well-being impact assessment of artificial intelligence – A search for causality and proposal for an open platform for well-being impact assessment of AI systems. *Evaluation and Program Planning, 99*, Article 102294. https://doi.org/10.1016/j.evalprogplan.2023.102294
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the*

Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
Hinds, P., & von Krogh, G. (2024). Generative AI, emerging Technology, and organizing: Towards a theory of progressive encapsulation. *Organization Theory*, (5), 1–14. https://doi.org/10.1177/26317877241293478
Hoffmann, M., Boysel, S., Nagle, F., Peng, S. & Xu, K. (2024). Generative AI and the nature of work. Harvard Business School Working Paper No. 25-021, CESifo Working Paper Series No. 11479. https://doi.org/10.2139/ssrn.5007084.
Huang, Y., & Gursoy, D. (2024). How does AI technology integration affect employees' proactive service behaviors? A transactional theory of stress perspective. *Journal of Retailing and Consumer Services, 77*, Article 103700. https://doi.org/10.1016/j.jretconser.2023.103700
Hwang, H., Sarstedt, M., Cheah, J. H., & Ringle, C. M. (2020). A concept analysis of methodological research on composite-based structural equation modeling: Bridging PLSPM and GSCA. *Behaviormetrika, 47*(1), 219–241. https://doi.org/10.1007/S41237-019-00085-5
Innocenti, S., & Golin, M. (2022). Human capital investment and perceived automation risks: Evidence from 16 countries. *Journal of Economic Behavior & Organization, 195*, 27–41. https://doi.org/10.1016/j.jebo.2021.12.027
Johnson, M., Albizri, A., & Harfouche, A. (2023). Responsible artificial intelligence in healthcare: Predicting and preventing insurance claim denials for economic and social wellbeing. *Information Systems Frontiers, 25*(6), 2179–2195. https://doi.org/10.1007/s10796-021-10137-5
Jones, N., Witze, A., Tollefson, J., & Kozlov, M. (2025). Science under trump 2.0: The likely winners and loser. *Nature, 637*, 532–535. https://doi.org/10.1038/d41586-025-00052-z
Jöreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika, 36*(4), 409–426. https://doi.org/10.1007/BF02291366
Kettlewell, N., Morris, R. W., Ho, N., Cobb-Clark, D. A., Cripps, S., & Glozier, N. (2020). The differential impact of major life events on cognitive and affective wellbeing. *SSM-Population Health, 10*, Article 100533. https://doi.org/10.1016/j.ssmph.2019.100533
Keyes, C. L. (2002). The mental health continuum: From languishing to flourishing in life. *Journal of Health and Social Behavior*, 207–222. https://doi.org/10.2307/3090197
Koeszegi, S.T. (.2024). AI@ work: Human empowerment or disempowerment?. In Werthner, H., Ghezzi, C., Kramer, J., Nida-Rümelin, J, Nuseibeh, B. & Prem, E (eds), Introduction to digital humanism, Springer, 175–196. https://doi.org/10.1007/978-3-031-45304-5_12.
Köhler, C., & Hartig, J. (2024). ChatGPT in higher education: Measurement instruments to assess student knowledge, usage, and attitude. *Contemporary Educational Technology, 16*(4), ep528. https://doi.org/10.30935/cedtech/15144
Koo, B., Curtis, C., & Ryan, B. (2021). Examining the impact of artificial intelligence on hotel employees through job insecurity perspectives. *International Journal of Hospitality Management, 95*, Article 102763. https://doi.org/10.1016/j.ijhm.2020.102763
Lacković, N. (2019). *Graduate employability (GE) paradigm shift: Towards greater socio-emotional and eco-technological relationalities of graduates' futures*. Education and technological unemployment. https://doi.org/10.1007/978-981-13-6225-5_13, 193-212.
Lam, S. S., Yik, M. S., & Schaubroeck, J. (2002). Responses to formal performance appraisal feedback: The role of negative affectivity. *Journal of Applied Psychology, 87* (1), 192. https://doi.org/10.1037/0021-9010.87.1.192
Leonard, P., & Tyers, R. (2021). Engineering the revolution?. *Imagining the role of new digital technologies in infrastructure work futures. new technology, work and employment* (pp. 1–20). https://doi.org/10.1111/ntwe.12226
Li, N., Zhou, H., & Mikel-Hong, K. (2024). Generative AI enhances team performance and reduces need for traditional teams. arXiv preprint arXiv:2405.17924. https://doi.org/10.48550/arXiv.2405.17924.
Lingmont, D. N. J., & Alexiou, A. (2020). The contingent effect of job automating technology awareness on perceived job insecurity: Exploring the moderating role of organizational culture. *Technological Forecasting and Social Change, 161*, Article 120302. https://doi.org/10.1016/j.techfore.2020.120302
Lozie, D. R., Omasa, R., Hesami, S., Zaman, S., Kajbaf, M., & Malik, A. R. (2024). Examining the impact of generative artificial intelligence on work dynamics. *Human Resources Management and Services, 6*(2). https://doi.org/10.18282/hrms.v6i2.3420, 3420-3420.
McDonald, T. (2024). Do generative artificial intelligence company strategies of 'moving fast and breaking things' in civil society cancel their social licence to operate? A nurse's evaluation of chatbot impacts. *Pacific Rim International Journal of Nursing Research, 28*(4), 689–706. https://doi.org/10.60099/prijnr.2024.268964
Muhammad, L., Amin, M., Khattak, A. Z., Mehsud, A. K., & Mustafa, R. (2022). The impact of leadership styles on employee wellbeing and resilience during COVID-19: A partial least square approach. *Reviews of Management Sciences, 4*(2), 1–13.
Müller, R., Locatelli, G., Holzmann, V., Nilsson, M., & Sagay, T. (2024). Artificial Intelligence and Project Management: Empirical overview, State of the art, and guidelines for future research. *Project Management Journal, 55*(1), 9–15. https://doi.org/10.1177/87569728231225198
Nussbaum, M. C., & Sen, A. (1993). *The quality of life*. Oxford University Press.
O'Boyle, E. H.jr., Humphrey, R. H., Pollack, J. M., Hawver, T. H., & Story, P. A. (2011). The relation between emotional intelligence and job performance: A meta-analysis. *Journal of Organizational Behavior, 32*(5), 788–818. https://doi.org/10.1002/job.714
OECD. (2011). *How's life? measuring well-being.* OECD Publishing.
OECD. (2020). *How's life? 2020: Measuring well-being.* https://doi.org/10.1787/9870c393-en. OECD.
Orji, J., Chan, G., Ndulue, C., & Orji, R. (2024). SmileApp: The design and evaluation of an mHealth app for stress reduction through artificial intelligence and persuasive technology. In *International Conference on Persuasive Technology* (pp. 237–251). Cham: Springer Nature Switzerland.
Papadopoulos, C., Castro, N., Nigath, A., Davidson, R., Faulkes, N., Menicatti, R., & Sgorbissa, A. (2022). The CARESSES randomised controlled trial: Exploring the health-related impact of culturally competent artificial intelligence embedded into socially assistive robots and tested in older adult care homes. *International Journal of Social Robotics, 14*(1), 245–256. https://doi.org/10.1007/s12369-021-00781-x
Parteka, A., Wolszczak-Derlacz, J., & Nikulin, D. (2024). How digital technology affects working conditions in globally fragmented production chains: Evidence from Europe. *Technological Forecasting and Social Change, 198*, Article 122998. https://doi.org/10.1016/j.techfore.2023.122998
Popescu, I. A., & Reis Mourão, P. (2025). Intertwining perspectives on happiness and well-being to explain the rise of creative cities. *Applied Research in Quality of Life*, 1–29. https://doi.org/10.1007/s11482-024-10417-7
Popescu, I.A., Stam, A.K.L. (2025). Exploring the dynamics of the twin transition in organizations: Fostering innovation through digital and green behavior development among employees. In: Visvizi, A., Troisi, O., Corvello, V., Grimaldi, M. (eds) Research and Innovation Forum 2024. RIIFORUM 2024. Springer Proceedings in Complexity. Springer, Cham. https://doi.org/10.1007/978-3-031-78623-5_50.
Puranam, P. (2021). Human–AI collaborative decision-making as an organization design problem. *Journal of Organization Design, 10*(2), 75–80. https://doi.org/10.1007/s41469-021-00095-2
Revell, G. (2024). Generative AI applications in the health and well-being domain: Virtual and robotic assistance and the need for niche language models (NLMs). In Z. Lyu (Ed.), *Applications of generative AI*. Cham: Springer. https://doi.org/10.1007/978-3-031-46238-2_9.
Sallam, M., Elsayed, W., Al-Shorbagy, M., Barakat, M., El Khatib, S., Ghach, W., & Malaeb, D. (2024, August). ChatGPT usage and attitudes are driven by perceptions of usefulness, ease of use, risks, and psycho-social impact: A study among university students in the UAE. In Frontiers in Education, (9), p. 1414758). https://doi.org/10.3389/feduc.2024.1414758.
Sarstedt, M., Hair, J. F., Jr, Cheah, J. H., Becker, J. M., & Ringle, C. M (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian marketing journal, 27*(3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003
Sarstedt, M., & Mooi, E. A. (2019). *A concise guide to market research: The process, data, and methods using ibm spss statistics*. Berlin: Springer, 3rd ed.
Sedkaoui, S. and Benaichouba, R. (2024), "Generative AI as a transformative force for innovation: A review of opportunities, applications and challenges", European Journal of Innovation Management, ahead-of-print(ahead-of-print). https://doi.org/10.1108/EJIM-02-2024-0129.
Shahzad, M. F., Xu, S., Liu, H., & Zahid, H. (2025). Generative artificial intelligence (ChatGPT-4) and social Media impact on academic performance and psychological well-being in China's Higher education. *European Journal of Education, 60*. https://doi.org/10.1111/ejed.12835. e12835.
Sharma, P. N., Liengaard, B. D., Hair, J. F., Sarstedt, M., & Ringle, C. M. (2023). Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT. *European journal of marketing, 57* (6), 1662–1677. https://doi.org/10.1108/EJM-08-2020-0636
Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European journal of marketing, 53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189
Sison, A. J. G., Daza, M. T., Gozalo-Brizuela, R., & Garrido-Merchán, E. C. (2024). ChatGPT: More than a "weapon of mass deception" ethical challenges and responses from the human-centered artificial intelligence (HCAI) perspective. *International Journal of Human–Computer Interaction,, 40*(17), 4853–4872. https://doi.org/10.1080/10447318.2023.2225931
Smaliukiene, R., & Bekesiene, S. (2020). Towards sustainable human resources: How generational differences impact subjective wellbeing in the military? *Sustainability, 12*(23), Article 10016. https://doi.org/10.3390/su122310016
Smith, B., (2025, January 25) The golden opportunity for American AI. https://blogs.microsoft.com/on-the-issues/2025/01/03/the-golden-opportunity-for-american-ai/.
Somers, M., (2024) How generative AI can boost highly How generative AI can boost highly skilled workers' productivity, https://mitsloan.mit.edu/ideas-made-to-matter/how-generative-ai-affects-highly-skilled-workers.
Stackpole, B., (2024) Leading the AI-driven organization. https://mitsloan.mit.edu/ideas-made-to-matter/leading-ai-driven-organization.
Suseno, Y., Chang, C., Hudik, M., & Fang, E. S. (2022). Beliefs, anxiety and change readiness for artificial intelligence adoption among human resource managers: The moderating role of high-performance work systems. *The International Journal of Human Resource Management, 33*(6), 1209–1236. https://doi.org/10.1080/09585192.2021.1931408
Suseno, Y., Chang, C., Hudik, M., & Fang, E.S. (.2023). Beliefs, anxiety and change readiness for artificial intelligence adoption among human resource managers: The moderating role of high-performance work systems. In Artificial intelligence and international hrm (pp. 144–171). Routledge.
Tani, M., Troise, C., & O'Driscoll, A. (2022). Business model innovation in mobile apps market: Exploring the new subscription plans with a behavioral reasoning perspective. *Journal of Engineering and Technology Management, 63*, Article 101674. https://doi.org/10.1016/j.jengtecman.2022.101674
Tekleab, A. G., Quigley, N. R., & Tesluk, P. E. (2009). A longitudinal study of team conflict, conflict management, cohesion, and team effectiveness. *Group & organization management, 34*(2), 170–205. https://doi.org/10.1016/j.jengtecman.2022.101674

Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., & Stewart-Brown, S. (2007). The Warwick-Edinburgh mental well-being scale (WEMWBS): Development and UK validation. *Health and Quality of life Outcomes, 5*, 63. https://doi.org/10.1186/1477-7525-5-63, 2007.

Tong, S., Jia, N., Luo, X., & Fang, Z. (2021). The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. *Strategic Management Journal, 42*(9), 1600–1631. https://doi.org/10.1002/smj.3322

Troth, A. C., Jordan, P. J., Lawrence, S. A., & Tse, H. H. (2012). A multilevel model of emotional skills, communication performance, and task performance in teams. *Journal of Organizational Behavior, 33*(5), 700–722. https://doi.org/10.1002/job.785

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative Science Quarterly, 42*(1), 35–67. https://doi.org/10.2307/2393808

Vanhove, A.J., .& Herian, M.N. (.2015). Team cohesion and individual wellbeing: A conceptual analysis and relational framework. In Team cohesion: Advances in psychological theory, methods and practice (pp. 53–82). Emerald Group Publishing Limited.

Veenhoven, R. (2012). Happiness: Also known as life satisfaction and subjective well-being. In K.C. Land, A. C. Michalos, & M. J. Sirgy (Eds.), Handbook of social indicators and quality of life research (pp. 63–77). Springer Netherlands. https://doi.org/10.1007/978-94-007-2421-1_3.

Wenger, E. (2000). Communities of practice and social Learning systems. *Organization, 7*(2), 225–246. https://doi.org/10.1177/135050840072002

Xu, S., & Wang, Z. (2021). The immediate and delayed impact of multitasking on well-being: An experience sampling study. *Human Behavior and Emerging Technologies, 3*(5), 710–719. https://doi.org/10.1002/hbe2.323

Zhang, C. B., Li, T. G., Li, Y. N., Chang, Y., & Zhang, Z. P. (2024). Fostering well-being: Exploring the influence of user-AI assistant relationship types on subjective well-being. *International Journal of Information Management, 79*, Article 102822. https://doi.org/10.1016/j.ijinfomgt.2024.102822