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MDDM

Master Degree Program in

Data-Driven Marketing

AI vs HR-Led Well-Being Interventions and Employee Well-Being: The Mediating Role of Perceived Organizational Support

Ioanna Novrouzai

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Marketing Research and CRM.

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May, 2025

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, May 2025

Ioanna Novrouzai

DEDICATION/ ACKNOWLEDGEMENTS

I would like to dedicate my thesis to my family. To my real-life heroes, my parents Marianna and Agron and to my loving sister Eva for always believing in me, supporting and inspiring me.

Firstly, I would like to thank my dear professors Diego and Mariana for their guidance and true mentoring. I am very proud that I had the chance to work with them.

I would also like to show my appreciation in my small community of people in Lisbon for making my journey and achievements here a blessing.

Finally, do not forget the words from Hill *"Whatever the Mind can conceive and believe, the Mind can achieve*".

ABSTRACT

This study explores how the source of workplace well-being interventions, AI-led versus HR-led, affects employee stress levels and well-being, with a focus on the mediating role of perceived organizational support (POS) and the moderating effect of existing well-being programs. Using an experimental vignette design (N = 175), participants were randomly assigned to experience either an AI- or HR-led well-being scenario. Findings reveal that while the type of intervention did not directly affect employee well-being or stress levels, perceived organizational support significantly mediated these outcomes. Employees who perceived higher support from their organization, regardless of intervention type, reported greater well-being and lower stress. Furthermore, the presence of a formal well-being program strengthened the positive relationship between HR-led interventions and POS, but had a weaker effect in the AI-led condition. These results underscore the psychological mechanisms through which interventions operate, suggesting that how support is perceived may matter more than the format of delivery. The study contributes to growing research on workplace AI by emphasizing that the success of tech-enabled interventions depends on cultural context, employee trust, and organizational care structures.

KEYWORDS

Employee Well-Being; Perceived Organizational Support; HR Interventions; AI in the workplace; workplace stress

Sustainable Development Goals (SDG): 

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
APA	American Psychological Association
EAP	Employee Assistant Program
HR	Human Resources
HRM	Human Resources Management
POS	Perceived Organizational Support
SPSS	Statistical Package for the Social Sciences
WHO	World Health Organization

1. INTRODUCTION

The increasing integration of artificial intelligence (AI) into workplace processes is reshaping how organizations approach not only efficiency and automation but also the structure and culture of work. In recent years, AI has begun to play an expanding role in areas traditionally managed by human resources, including employee well-being, engagement, and mental health support (Dwivedi et al., 2021). According to a report by McKinsey & Company (2022), over half of organizations worldwide are now using AI in various capacities, from automating workflows to supporting strategic decision-making. This digital shift coincides with a surge in workplace stress, burnout, and emotional strain. The COVID-19 pandemic has further accelerated these challenges, introducing more complex work environments characterized by hybrid models, digital overload, and social isolation (Kniffin et al., 2021; Oakman et al., 2020).

These developments have created an urgent need for scalable and adaptive well-being interventions that extend beyond conventional HR practices. Chronic stress and mental fatigue now pose serious risks not only to individual employees but also to organizational productivity and sustainability (Cooper & Lu, 2022). The World Health Organization (2022) has identified workplace stress as a leading cause of mental health disorders, contributing to an estimated one trillion dollars in lost productivity globally each year. Similarly, data from the American Institute of Stress (2023) highlights growing employee disengagement and absenteeism linked to unmanaged psychological strain.

In response, organizations are increasingly adopting innovative technologies aimed at supporting employee well-being in real time. These include generative AI assistants capable of offering immediate support, and behavioral analytics tools that attempt to identify emotional states through various data inputs (Onyeka Omose & Kehinde Ikuyinminu, 2024). The growing use of artificial intelligence in the workplace well-being initiatives has opened new possibilities for supporting employees, yet important questions remain about how these tools are perceived and whether they are truly effective. While AI technologies such as generative assistants may reduce stress by offering scalable support, their success depends on more than just technical performance. Employees' perceptions of authenticity and care, as well as the organization's intent, play a key role in shaping outcomes (Strohmeier & Piazza, 2015; Gartner, 2023). Research in this area is still emerging and tends to focus on clinical settings, with limited evidence on how AI interventions work in everyday organizational contexts (Brynjolfsson & McAfee, 2017; Dwivedi et al., 2021). Moreover, although perceived organizational support is known to improve well-being (Eisenberger et al., 1986), its role in mediating responses to AI-led support has received little attention. These gaps highlight the need to better understand not only the type of intervention used, but also how it is delivered, perceived, and shaped by the wider organizational environment.

This study offers two key contributions to the literature, providing both theoretical insights and practical value for organizations aiming to enhance employee well-being in increasingly digital work environments. First, it advances understanding of AI-led well-being interventions by comparing their effectiveness in reducing employee stress to that of traditional HR-led approaches. While much of the prior literature has emphasized AI's operational efficiencies, this study shifts the focus to its psychological impact, particularly in the context of organizational care (Dwivedi et al., 2021). By incorporating perceived organizational support (POS) as a mediating variable, the research extends established models of employee well-being, illustrating how the source of support—whether technological or human—can influence stress-related outcomes (Eisenberger et al., 1986; Caesens & Stinglhamber, 2014).

Second, this study addresses important gaps by proposing and empirically testing a conceptual model that integrates intervention type, POS, and formal well-being infrastructure. It demonstrates that the success of any intervention depends not only on its format but also on how it aligns with existing organizational practices and cultural signals. The presence of formal well-being programs is explored as a moderator, offering new insight into how organizational context can amplify or undermine the perceived value of support strategies.

The findings are intended to guide HR professionals, organizational leaders, and people analytics teams, while also offering relevance for marketing leaders focused on employer branding and employee experience in data-driven workplaces. By highlighting the psychological dimensions of technological interventions, the study encourages a more integrated and empathetic approach to organizational well-being.

2. LITERATURE REVIEW

2.1 Workplace and HR

2.1.1 The Evolving Role of HR and the Workplace Context

Over the past two decades, the nature of work and the role of human resource management (HRM) have undergone significant transformation. As organizations become more dynamic, globalized, and technology-driven, HR is increasingly tasked with not only managing talent and performance but also enhancing the broader employee experience (Tursunbayeva et al., 2018). This shift has expanded the HR function beyond administrative tasks to include responsibility for employee well-being, mental health, and organizational culture.

In parallel, workplaces themselves have been shaped by sociotechnical shifts, including the rise of hybrid work, increased digitization, and new expectations around work-life balance. The COVID-19 pandemic further accelerated these changes, highlighting the vulnerabilities in employee support systems and prompting organizations to seek more agile and scalable well-being strategies (Kniffin et al., 2021). As a result, the intersection of HR practices and workplace well-being has become a central focus in organizational research and practice.

This literature review explores current research related to employee stress and organizational responses to well-being needs, with a particular focus on the comparative impact of AI-led and HR-led interventions. Special attention is given to the role of perceived organizational support as a psychological mechanism and the influence of organizational context in shaping employee responses. The review is organized into five key areas: employee stress and well-being, traditional HR-led interventions, the emergence of AI in HR, AI-led well-being interventions, and the mediating and moderating variables that inform their effectiveness.

By synthesizing these strands of literature, on how organizations can balance technological innovation with employee-centered care.

2.1.2 The Emergence of Artificial Intelligence in Human Resource Management

Artificial Intelligence (AI) has emerged as a transformative force across various organizational functions, including marketing, finance, operations, and increasingly, human resource management (HRM). Within HR, AI technologies are being applied to a range of activities such as recruitment, performance evaluation, talent analytics, and employee engagement (Tambe et al., 2019; Tursunbayeva et al., 2018). These applications are changing not only the speed and efficiency of HR operations but also how employees experience organizational support and interaction.

AI's potential in HR lies in its ability to process vast amounts of data, identify patterns, and generate predictive insights that inform decision-making (Dwivedi et al., 2021). For example, AI can assist with shortlisting candidates based on predefined success indicators or identify disengagement signals from communication patterns. In doing so, it allows HR professionals to focus more on strategic, high-touch tasks while delegating routine and data-intensive functions to machines.

However, the integration of AI into HR processes is not without controversy. Scholars have raised concerns about fairness, transparency, data privacy, and the risk of algorithmic bias, particularly when AI systems are used to make or influence personnel decisions (Sánchez et al., 2022; (Strohmeier & Piazza, 2015). There is also growing attention on the psychological impact of interacting with AI in sensitive domains such as mental health and well-being, where human empathy and trust play a critical role.

Despite these concerns, the growing adoption of AI in HR reflects broader trends in digital transformation and the pursuit of scalable, cost-effective solutions to organizational challenges. In particular, AI-powered tools like generative AI assistants and employee sentiment analysis platforms are being explored for their potential to support employee well-being, either by offering proactive advice or responding to mental health cues in real time (Gong et al., 2024a). Yet, empirical research remains limited on how these technologies compare with traditional human-led approaches in their ability to influence psychological outcomes such as stress reduction.

This emerging area of inquiry calls for a deeper understanding of how AI is reshaping the HR landscape not just operationally, but relationally. As organizations increasingly rely on AI to mediate employee experience, it becomes critical to examine how these tools are perceived by workers, and whether they enhance or undermine key psychological constructs such as trust, fairness, and perceived organizational support.

2.2 Employee Well-Being and Stress in the Workplace

Employee well-being has become a central concern in organizational research and practice, particularly as the nature of work evolves. Well-being in the workplace refers to a holistic state in which individuals experience physical, emotional, and psychological health, enabling them to perform optimally while maintaining life satisfaction and resilience (Cooper & Lu, 2022). It encompasses various dimensions, including job satisfaction, engagement, work-life balance, and mental health. Increasingly, organizations are recognizing that supporting employee well-being is not only a moral imperative but also a strategic necessity, as it is closely linked to performance, retention, and organizational commitment (Sonnentag & Frese, 2013).

One of the most pressing threats to employee well-being is workplace stress. Stress is defined as the psychological and physiological response to demands that exceed an individual's coping resources (Lazarus & Folkman, 1984). Chronic work-related stress has been consistently linked to a range of adverse outcomes, including burnout, increased absenteeism, reduced job satisfaction, and diminished performance across various professional environments (Nübling, Vomstein, & Mühlbacher, 2014). According to the World Health Organization (2022), workplace stress is one of the leading causes of mental health disorders, contributing to over one trillion dollars in lost productivity each year.

The COVID-19 pandemic has further intensified stress levels across sectors. Remote and hybrid work models, while offering flexibility, have blurred boundaries between professional and personal life, often leading to digital overload, isolation, and increased emotional strain (Kniffin et al., 2021; Oakman et al., 2020). These shifts have reshaped employee expectations and revealed the inadequacy of many traditional well-being approaches in managing ongoing stress and burnout in dynamic work environments.

The growing complexity of workplace demands has highlighted the importance of proactive, scalable, and psychologically attuned well-being interventions. While many organizations have implemented programs to address stress, ranging from mindfulness training to flexible scheduling, their effectiveness varies depending on contextual and individual factors (Cooper & Lu, 2022). These challenges call for more innovative and responsive approaches to supporting well-being, especially those that are integrated into the daily experiences of employees rather than treated as add-on initiatives.

Understanding the roots and consequences of stress is foundational to evaluating the role of different intervention strategies, including the emerging use of artificial intelligence. As this field evolves, it becomes essential to explore how both traditional and technology-enabled approaches can mitigate stress while reinforcing a culture of care and support within organizations.

2.2.1 Traditional HR-Led Well-Being Interventions

Human resource-led well-being interventions have long served as the primary means by which organizations support the mental and emotional health of their employees. These interventions typically include programs such as employee assistance programs (EAPs), counseling services, mindfulness workshops, health screenings, stress management training, and flexible work policies (Cooper & Lu, 2022). The aim of the interventions is to prevent or alleviate work-related stress, promote psychological resilience, and enhance overall employee satisfaction and engagement.

Research has shown that these traditional approaches can be effective when well-designed and consistently applied. For instance, employee assistance programs have been associated with reduced absenteeism and improved job performance, particularly when employees feel confident in the confidentiality and accessibility of such services (Attridge, 2019). Similarly, training programs that focus on emotional regulation, time management, and resilience have been linked to improvements in psychological well-being and reductions in perceived stress (Richardson & Rothstein, 2008).

However, despite their potential, traditional HR-led interventions are often limited in their scalability, responsiveness, and personalization. Many of these programs are resource-intensive, requiring trained facilitators, significant time investment, and ongoing managerial support. In fast-paced or digitally distributed work environments, such interventions may not be flexible or timely enough to meet individual employee needs (Sonnentag & Frese, 2013). Furthermore, participation rates can be low due to stigma, lack of awareness, or perceived irrelevance to one’s immediate challenges (Noblet & LaMontagne, 2006).

A growing concern in the literature is the misalignment between organizational initiatives and employee perceptions of care. When well-being programs are implemented in a performative or reactive manner, employees may view them as insincere, which can erode trust and reduce program effectiveness (Guest, 2017). In contrast, interventions that are perceived as authentic and embedded in the organization’s culture tend to foster greater perceived organizational support and emotional engagement (Rhoades & Eisenberger, 2002).

Ultimately, while HR-led interventions provide a foundation for organizational well-being efforts, their limitations have prompted interest in more innovative, scalable, and integrated approaches. This includes exploring how digital technologies, including artificial intelligence, might complement or enhance the impact of human-led support mechanisms.

Given the relational nature of HR-led interventions and the perceived impersonality of AI tools, it is expected that the type of intervention will significantly influence how employees experience support and well-being.

2.2.2 Traditional AI-Led Interventions for Employee Well-Being

As artificial intelligence becomes more integrated into human resource management, one of its emerging applications is in the area of employee well-being. AI-led interventions are increasingly being designed to support mental health, emotional resilience, and stress management in the workplace. These tools include generative AI assistants that offer guided mental health check-ins, automated coaching platforms, digital well-being nudges, and intelligent dashboards that synthesize employee sentiment data to inform support strategies (Dutta & Sushanta Kumar Mishra, 2023)

Proponents argue that AI-led interventions provide unique advantages over traditional methods. They are often available on demand, scalable across large workforces, and capable of offering personalized responses based on real-time data (Dwivedi et al., 2021). In contrast to structured wellness programs, which often follow a one-size-fits-all model, AI tools can adapt content or delivery based on user preferences and behavioral cues. This flexibility makes them particularly appealing in hybrid and remote work environments, where real-time access to in-person support may be limited.

Despite these benefits, the effectiveness of AI-led well-being tools remains an open question. While early findings suggest that AI can reduce stress through automation and digital coaching, other studies highlight employee concerns around data privacy, emotional detachment, and a lack of human empathy ((Sánchez et al., 2022; Strohmeier & Piazza, 2015). These concerns are particularly relevant in the context of well-being, where trust and psychological safety are critical for engagement.

The psychological reception of AI-led interventions appears to hinge on how employees interpret their intent and authenticity. If AI tools are seen as genuine expressions of care, they may foster perceived organizational support and reduce stress. However, if perceived as surveillance or cost-saving substitutes for human interaction, they may backfire, leading to skepticism or disengagement (Gong et al., 2024a). This divergence highlights the importance of framing, implementation context, and cultural alignment in determining the success of AI-led well-being initiatives.

Moreover, empirical comparisons between AI-led and human-led interventions are scarce. Most existing research has either focused on AI's operational benefits or studied its role in stress detection rather than intervention. As a result, the field lacks robust evidence on whether AI-led tools are equally, more, or less effective than traditional HR-led strategies in improving well-being outcomes such as stress reduction, emotional engagement, and job satisfaction.

Therefore, Hypothesis 1 is proposed:

H1: Employees who receive a human-led well-being intervention will report higher levels of well-being than those who receive an AI-led intervention.

Given the increasing deployment of AI in employee support functions, it is crucial to examine not only its technical capabilities but also its psychological and relational impacts. More research is needed to understand the conditions under which AI-led interventions are most effective, how they interact with employee expectations, and whether they enhance or erode key factors such as perceived organizational support.

2.3 Perceived Organizational Support

Perceived Organizational Support (POS) is a foundational concept in organizational psychology, referring to employees' belief that their organization values their contributions and genuinely cares about their well-being (Eisenberger et al., 1986). Extensive research has shown that POS positively influences job satisfaction, employee engagement, performance, and psychological resilience while reducing turnover intentions and workplace stress (Rhoades & Eisenberger, 2002).

In the context of well-being strategies, POS functions as a key mediating mechanism. It shapes how employees interpret organizational initiatives, including those related to stress management and technological change. When interventions—whether human- or AI-led—are perceived as sincere and aligned with the organization's care values, employees are more likely to experience reduced stress and increased satisfaction (Caesens & Stinglhamber, 2014). In contrast, when support mechanisms are viewed as impersonal or performative, their impact on well-being may be limited or even negative (Guest, 2017).

The perceived source of support plays a critical role in shaping POS. Traditional HR-led interventions are typically experienced as more empathetic and relational, fostering emotional trust. In contrast, AI-led interventions may be met with skepticism or emotional distance, particularly if they are poorly integrated or perceived as impersonal. However, recent research suggests that when AI tools are deployed in the context of high organizational support and trust, employees may be more open to embracing these technologies and even benefit from them. For example, Marimon and Mas-Machuca (2024) found that trust in generative AI can enhance employee engagement and satisfaction, particularly when the organizational environment reinforces care and ethical use.

Despite the theoretical relevance of POS in the adoption of AI-led interventions, there is a notable gap in empirical studies that explicitly test its mediating role. Most research has either focused on the functional benefits of AI or addressed POS in relation to traditional HR strategies, without linking the two. This creates an opportunity for new studies to explore how employee perceptions of organizational care influence the reception and impact of AI-based well-being tools.

Building on the theoretical foundations of perceived organizational support, it is likely that employees' perceptions of how much the organization values and cares for them will explain the link between intervention type and well-being outcomes.

This leads to Hypothesis 2:

H2: Perceived organizational support will mediate the relationship between intervention type and employee well-being.

Understanding POS as a mediator offers valuable insight into how well-being interventions can be more effective. It emphasizes that how support is perceived is often just as important as what support is provided, especially in workplaces undergoing digital transformation.

2.4 Presence of Well-Being Programs

The success of workplace well-being interventions is not determined solely by their content or mode of delivery but is deeply shaped by the organizational context into which they are introduced. Among the most influential contextual factors is the presence or absence of established well-being or stress management programs. These programs create expectations and norms that influence how employees interpret new interventions, including those powered by artificial intelligence (Allen et al., 2010; Noblet & LaMontagne, 2006).

Organizations that have embedded well-being practices into their culture signal a long-term commitment to employee care. In such settings, employees are more likely to view new interventions, whether AI-led or HR-led, as meaningful extensions of an already supportive environment (Guest, 2017). These perceptions can foster trust, increase perceived organizational support, and enhance the effectiveness of the intervention itself (Rhoades & Eisenberger, 2002). In contrast, in organizations without such structures, even well-designed interventions may be met with doubt or disinterest. Employees may interpret them as cost-cutting measures or superficial responses rather than genuine attempts to improve their well-being (Biron & van Veldhoven, 2012).

Context also plays a critical role in shaping how technology is received. Research has shown that environments characterized by transparency, trust, and participatory culture are more conducive to the acceptance of new tools, particularly those that involve personal or emotional dimensions (Strohmeier & Piazza, 2015; Marimon & Mas-Machuca, 2024). When AI is introduced in workplaces with minimal well-being infrastructure, it may be perceived as a depersonalized substitute for human support. Conversely, in supportive environments, the same AI tools may be welcomed as scalable enhancements to existing practices (Tambe et al., 2019; (Sánchez et al., 2022).

Despite the intuitive importance of context, few empirical studies have directly examined how the presence of formal well-being programs moderates the effectiveness of AI-led or HR-led interventions. This is a critical gap, particularly as more organizations adopt digital tools to manage employee well-being.

The effectiveness of any intervention may depend on the organizational environment in which it is introduced. When well-being programs are already in place, new initiatives may be received with greater trust and openness.

This study also accounts for the broader organizational context in which well-being interventions are delivered. The presence of a formal well-being program is likely to influence how employees perceive and evaluate both AI-led and HR-led initiatives. When such programs exist, these interventions may be interpreted as part of a consistent and credible organizational commitment to employee care, thereby strengthening perceptions of organizational support. On the other hand, in the absence of a formal program, interventions, particularly those led by artificial intelligence, may appear isolated, impersonal, or lacking authenticity, potentially diminishing their perceived value and effectiveness.

It is therefore anticipated that the impact of intervention type on perceived organizational support will be contingent upon whether a structured well-being program is already in place.

This leads to the following hypothesis:

H3: The presence of a formal well-being program will moderate the relationship between intervention type and perceived organizational support, such that the effect will be stronger in organizations where such a program exists.

Exploring this moderating relationship can help explain the variability in intervention outcomes across different organizational settings and offer practical guidance for more strategic implementation.

To synthesize the theoretical foundations and gaps discussed throughout this chapter, the following research model (figure 1) has been developed. It illustrates the proposed relationships between the type of well-being intervention (AI-led vs. HR-led) and employee well-being, with perceived organizational support acting as a mediator, and the integration of well-being programs as a moderator.

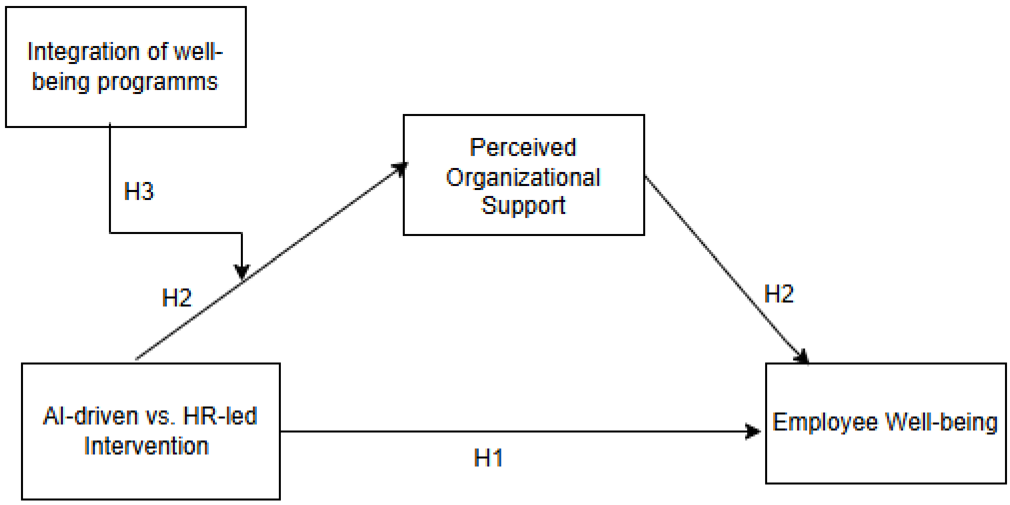

Figure 1. *Research Model*

3. EMPIRICAL STUDY

Our theoretical framework makes several predictions that we empirically test. First, we investigate the causal effect of intervention type (AI-led vs. HR-led well-being support) on employee outcomes, including both employee well-being. While well-being reflects positive psychological states such as satisfaction, engagement, and emotional resilience, stress reflects the negative strain experienced in response to workplace demands. Together, these outcomes provide a balanced view of how employees react to different sources of well-being support.

Second, we explore whether perceived organizational support (POS) explains the effects of intervention type on employee outcomes. POS refers to the extent to which employees believe their organization values their contributions and cares about their well-being. When employees perceive an intervention as being motivated by genuine organizational concern, POS is likely to increase, which in turn may enhance well-being and reduce stress. This mediating mechanism helps uncover the psychological pathway through which the intervention source influences employee experience.

Third, we examine whether the effect of intervention type (AI-led vs. HR-led) on perceived organizational support is context-dependent. Specifically, we propose that the relationship will be moderated by the presence of existing organizational well-being or stress management programs

We test these predictions through an experimental study. The design and procedures were preregistered (AsPredicted #229925).

3.1 Data

Our study uses a single-factor (intervention type: AI-led vs. HR-led well-being intervention) scenario-based, between-subjects experiment. A total of two hundred and sixty-nine participants were recruited in Portugal via social media on a voluntary basis. We excluded participants who failed the attention check (*n* = 20), leaving the final sample including 175 participants (58.3% female, 40.6% male, 1.1% other; M_{age} = 30.85, *SD* = 6.48) as shown in Tables 1 and 2 below.

Table 1

Gender Distribution of Participants

Please indicate your gender.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	71	40,6	40,6	40,6
	Female	102	58,3	58,3	98,9
	Other	2	1,1	1,1	100,0
	Total	175	100,0	100,0	

Table 2

Descriptive Statistics for Participant Age

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age (in years)	175	20,00	57,00	30,85	6,48
Valid N (listwise)	175				

3.2 Procedures

This study employed a vignette based experimental design to simulate workplace experiences involving stress and organizational support interventions. Vignettes are a widely used method in behavioral research that enables researchers to manipulate hypothetical conditions while maintaining ecological validity (Aguinis & Bradley, 2014). Participants were randomly assigned to read one of two scenarios describing an intervention introduced by their organization to address ongoing workplace stress.

In the AI-led intervention condition, participants read about an organization that had implemented a digital well-being system designed to analyze stress levels through interaction monitoring and provide personalized mental health recommendations. The system offered automated support, including mindfulness app suggestions, virtual coaching, and reminders tailored to behavioral patterns. This scenario reflects contemporary applications of AI in workplace wellness, which promise scalable, data-driven mental health support (Tambe et al., 2019; Marimon & Mas-Machuca, 2024).

In the HR-led intervention condition, participants imagined that their organization had introduced a more traditional support structure, managed directly by HR staff. The vignette described weekly workshops, mindfulness sessions, and in-person group discussions on stress management, all coordinated manually by human staff. These types of interventions are consistent with conventional organizational responses to psychological strain and reflect employee assistance practices that have been widely used over the past several decades (Attridge, 2019; Cooper & Lu, 2022).

Both scenarios were constructed to ensure equal stress severity and parallel positive intervention outcomes, allowing for an isolated examination of how the source of the intervention, AI vs. HR, affects employee perceptions and well-being. The vignettes ended by stating that participants experienced a reduction in stress and an improvement in well-being, thereby enhancing consistency in expected outcomes and allowing a focused test of the hypothesized mediating and moderating effects (Aguinis & Bradley, 2014).

The study was conducted in English. The full stimulus texts used in the experiment are provided in Appendix A.

3.3. Measures

We assessed all variables using a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). Our primary dependent variable, *Employee Well-Being*, was measured using a five-item scale adapted from Diener et al. (2009) (α = .91). This scale captures general positive psychological functioning and satisfaction with life at work.

We also included an additional dependent variable, Employee Stress Levels *(ESL)*, measured using a five-item scale adapted from Cohen et al. (1983) (α = .86). This scale reflects perceived stress and emotional strain resulting from workplace demands.

Our mediating variable, *Perceived Organizational Support (POS)*, was measured using a six-item scale based on Eisenberger et al. (1986) (α = .94). This scale assesses the extent to which employees believe their organization values their contributions and cares about their well-being.

To validate the experimental manipulation, participants answered one item verifying their recognition of the intervention type (AI-led vs. HR-led well-being support). Participants also rated the realism of the scenario using one item to assess external validity. Demographic questions (e.g., age, gender, position level) were included at the end of the survey.

All measures exceeded the recommended reliability threshold of 0.70 (Nunnally & Bernstein, 1994). See APPENDIX B1 for full reliability statistics.

3.3 Analyses

To investigate the effects of the type of intervention on employee well-being (H1), we conducted an independent samples t-test. The type of intervention (X) served as the independent variable – coded as 1 = HR-led, 2 = AI-led – and employee well-being as the dependent variable (Y).

To explore the mediating role of perceived organizational support on employee well-being (H2), we used PROCESS Model 4 with 5,000 bootstrapped samples and a 95% confidence interval (Hayes, 2022). The type of intervention served as the independent variable (X); perceived organizational support as the mediator (M); and employee well-being as the dependent variable (Y).

To investigate the moderation effects of the presence of a well-being program on perceived organizational support (H3), we conducted a two-way ANOVA. Perceived organizational support (Y) served as the dependent variable, and both the intervention type and the presence of an organizational well-being program were entered as between-subjects factors.

To test whether the presence of a formal well-being program moderates the indirect effect of intervention type on employee well-being via perceived organizational support, a moderated mediation analysis was conducted using the PROCESS macro for SPSS (Model 7; Hayes, 2022), with 5,000 bootstrap resamples and 95% confidence intervals. In this model, intervention type (0 = HR-led, 1 = AI-led) served as the independent variable (X), perceived organizational support as the mediator (M), employee well-being as the outcome (Y), and the presence of a well-being program as the moderator (W) of the first stage.

4. RESULTS

4.1 Manipulation checks

Results confirmed that the manipulation was successful. An independent samples t-test showed that participants in the HR-led condition reported significantly higher agreement with the statement "The well-being intervention was manually managed by HR" (M_{HR} =4.64, *SD* = 1.47) than participants in the AI-led condition (M_{AI} = 3.38, SD = 1.77), $t(166.609) = 5.10$, $p < .001$ (See Tables 4 & APPENDIX B2).

Similarly, the results indicate participants in the AI-led condition showed significantly higher agreement with the statement "The workplace intervention involved AI" (M_{AI} = 4.71, *SD* = 1.95) compared to those in the HR-led condition (M_{hr} = 3.18, SD = 1.80), $t(171.487) = -5.39$, $p < .001$. The corresponding effect size was also large, Cohen's *d* = -0.82 (95% *CI* [-1.123, -0.506]) (See Table 4).

Table 4

Group Statistics for Manipulation Check Items

Group Statistics

	SCENARIO	N	Mean	Std. Deviation	Std. Error Mean
Taking into account the scenario you read, to what extent do you agree with the following statements? - The well-being intervention was manually managed by HR	HR	88	4,64	1,47	,157
	AI	87	3,38	1,77	,190
Taking into account the scenario you read, to what extent do you agree with the following statements? - The workplace intervention involved AI	HR	88	3,18	1,80	,192
	AI	87	4,71	1,95	,209

These results confirm that participants accurately identified the nature of the intervention based on the experimental condition, validating the effectiveness of the manipulation. Furthermore, responses to the realism item ("The situation described in the scenario is realistic") indicated that the scenario was perceived as ecologically valid (*M* = 4.14, *SD* = 1.58), supporting the external credibility of the experimental vignette (Aguinis & Bradley, 2014). (see Table 5).

Table 5

Descriptive Statistics for Scenario Realism Evaluation

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
The situation described in the scenario is...	175	1	7	4,14	1,58
Valid N (listwise)	175				

4.2 Main Effect

4.2.1. Employee Well-Being

As predicted, we tested whether there was a significant main effect of intervention type on employee well-being. As shown in table 6, an independent samples t-test revealed that participants in the HR-led condition reported slightly higher well-being (*M* = 4.30, *SD* = 1.21) than participants in the AI-led condition (*M* = 4.25, *SD* = 1.20), but this difference was not statistically significant, $t(173) = 0.27$, $p = .787$. (see Table 7).

Table 6

Group Statistics for Employee Well-being by Intervention Type

Group Statistics

	SCENARIO	N	Mean	Std. Deviation	Std. Error Mean
EWB	HR	88	4,30	1,21	,12902
	AI	87	4,25	1,20	,12824

Table 7

Independent Samples t-Test for Employee Well-being

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
EWB	Equal variances assumed	,194	,660	,297	173	,383	,767	,05400	,18192	-,30507	,41306
	Equal variances not assumed			,297	173,000	,383	,767	,05400	,18191	-,30505	,41304

The effect size was negligible, Cohen's *d* = 0.05 (95% CI [−0.252, 0.341]). These findings do not support H1, suggesting that the type of intervention (HR-led vs. AI-led) did not significantly affect perceived employee well-being (See Table 8).

Table 8

Effect Sizes for Employee Well-being by Intervention Type

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
EWB	Cohen's d	1,20326	,045	-,252	,341
	Hedges' correction	1,20851	,045	-,250	,340
	Glass's delta	1,19610	,045	-,251	,341

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

4.2.2. Employee Stress Levels

Employee Stress Levels. Additionally, Employee Stress Levels were tested and according to Table 9, results show no significant main effect of intervention type on employee stress levels. Participants in the AI-led condition (*M* = 4.28, *SD* = 1.26) did not significantly differ from those in the HR-led condition (*M* = 4.16, *SD* = 1.12), *t*(170.392) = -0.68, *p* = .501. These findings suggest that while the type of intervention (AI-led vs. HR-led) may affect how employees interpret organizational support, it does not significantly influence their perceived stress levels in the short term (See Table 10).

Table 9

Group Statistics for Employee Stress Levels by Intervention Type

Group Statistics

	SCENARIO	N	Mean	Std. Deviation	Std. Error Mean
ESL	HR	88	4,16	1,12	,11964
	AI	87	4,28	1,26	,13472

Table 10

Independent Samples t-Test for Employee Stress Levels

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
ESL	Equal variances assumed	1,863	,174	-,674	173	,251	,501	-,12139	,18006	-,47680	,23401
	Equal variances not assumed			-,674	170,382	,251	,501	-,12139	,18018	-,47707	,23428

4.3. Mediation effect

4.3.1. Perceived Organizational Support (POS)

First, we assessed the effect of intervention type on perceived organizational support (the mediator). The overall model predicting POS was **not significant** (R^2 = .008, F(1,173) = 1.38, p = .242), suggesting that intervention type did not explain a significant proportion of variance in perceived organizational support. Additionally, the direct effect of intervention type on POS was **not significant** (β = –0.24, SE = 0.21, t(173) = –1.17, p = .242), indicating that participants' perceptions of support from the organization were similar across AI-led and HR-led conditions.

4.3.2. Employee Well-Being (EWB)

Next, we examined the effect of intervention type and POS on employee stress levels (the dependent variable). The overall model was **significant** (R^2 = .109, F(2,172) = 10.54, p < .001). POS significantly predicted lower stress levels (β = –0.29, SE = 0.06, t(172) = –4.53, p < .001). However, the direct effect of intervention type on employee stress levels remained non-significant when controlling for POS (β = 0.05, *SE* = 0.17, $t(172) = 0.31$, $p = .760$), suggesting that perceived organizational support may play a limited role in explaining the relationship.

The indirect effect of intervention type on employee well-being through POS was also **not significant**, as the confidence interval included zero (*Effect* = –0.131, *BootSE* = 0.114, 95% CI [–0.370, 0.083]). Thus, the mediation hypothesis (H2) was not supported for EWB.

The full MATRIX can be found in Appendix C.

4.3.3. Additional variables

Employee Stress Levels (ESL). Then additionally, we examined the effect of intervention type and POS on employee stress levels. The overall model was **significant** ($R^2 = .109$, $F(2, 172) = 10.54$, $p < .001$). POS was a significant negative predictor of stress levels (β = –0.29, *SE* = 0.06, $t(172) = -4.53$, $p < .001$), indicating that higher organizational support was associated with lower stress. However, the direct effect of intervention type on employee stress levels remained **not significant** when controlling for POS (β = 0.05, *SE* = 0.17, $t(172) = 0.31$, $p = .760$)), suggesting that perceived organizational support may play a limited role in explaining the relationship.

Finally, the analysis of the indirect effect of intervention type on stress levels through POS revealed a **non-significant** mediation (*Effect* = 0.069, *BootSE* = 0.065, 95% CI [–0.045, 0.215]).

Since the confidence interval includes zero, this suggests that perceived organizational support does not mediate the relationship between intervention type and employee stress levels.

The full MATRIX can be found in Appendix C.

4.4. Moderation effect

4.4.1. Implementation of well-being programs

Results of the two-way ANOVA revealed that the main effect of intervention type (AI-led vs. HR-led) on employee well-being was **not significant** (M_{HR} = 4.30, *SD* = 1.21 vs. M_{AI} = 4.25, *SD* = 1.20),

$F(1, 171) = 0.060$, $p = .807$. The main effect of program implementation (yes vs. no) was also **not significant** ($M_{yes} = 4.25$, $SD = 1.30$ vs. $M_{no} = 4.30$, $SD = 1.21$), $F(1, 171) = 0.056$, $p = .814$.

Importantly, there was a significant interaction effect between intervention type and program implementation on employee well-being, $F(1, 171) = 4.697$, $p = .032$.

Planned contrasts revealed that when a well-being program was implemented, participants in the HR-led condition reported significantly lower well-being ($M = 4.07$, $SD = 1.33$) compared to those in the AI-led condition ($M = 4.50$, $SD = 1.01$), suggesting that in the presence of a formal program, AI-led interventions were perceived more favorably. However, in the absence of such a program, no significant difference in well-being was observed between the two intervention types ($M_{HR} = 4.50$, $SD = 1.08$ vs. $M_{AI} = 4.06$, $SD = 1.21$), $F(1, 86) = 1.80$, $p = .183$ (See Tables 11 & 12).

These findings provide support for H3, indicating that the implementation of well-being programs moderates the effect of intervention type on employee well-being.

Table 11

Descriptive Statistics for Employee Well-being by Intervention Type and Program Integration

Descriptive Statistics

Dependent Variable: EWB

SCENARIO	Has your organization implemented well-being or stress management programs?	Mean	Std. Deviation	N
HR	Yes, it has.	4,07	1,33	40
	No, it has not.	4,50	1,08	48
	Total	4,30	1,21	88
AI	Yes, it has.	4,41	1,27	46
	No, it has not.	4,06	1,09	41
	Total	4,25	1,20	87
Total	Yes, it has.	4,25	1,30	86
	No, it has not.	4,30	1,10	89
	Total	4,28	1,20	175

Table 12

Between-Subjects Effects for Employee Well-being

Tests of Between-Subjects Effects

Dependent Variable: EWB

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	6,906[a]	3	2,302	1,615	,188
Intercept	3157,925	1	3157,925	2215,876	<,001
SCENARIO	,085	1	,085	,060	,807
External	,079	1	,079	,056	,814
SCENARIO * External	6,694	1	6,694	4,697	,032
Error	243,698	171	1,425		
Total	3449,480	175			
Corrected Total	250,604	174			

a. R Squared = ,028 (Adjusted R Squared = ,010)

4.4.2. Moderated Mediation

Results show that the interaction between intervention type and the integration of well-being programs was not significant (*β* = -0.417, *BootSE* = 0.414, *p* = 0.314, 95% CI [-1.234, 0.399]). In organizations without integrated well-being programs, the effect of intervention type on perceived organizational support was non-significant (*β* = -0.019, BootSE = 0.166, 95% CI [-0.341, 0.310]). In contrast, in organizations with integrated well-being programs, the effect was marginally significant and negative (*β* = -0.245, BootSE = 0.160, 95% CI [-0.573, 0.046]).

When examining the indirect effect of intervention type on employee well-being through perceived organizational support, we found a marginal conditional indirect effect only in the context of integrated well-being programs. Specifically, the conditional indirect effect was *β* = -0.245, *BootSE* = 0.160, 95% CI [-0.573, 0.046], whereas in the absence of such programs the indirect effect was negligible (*β* = -0.019, *BootSE* = 0.166, 95% CI [-0.341, 0.310]).

Finally, the index of moderated mediation was not statistically significant (Index = -0.226, *BootSE* = 0.229, 95% CI [-0.702, 0.205]), indicating that the indirect effect of intervention type on employee well-being via perceived organizational support did not significantly differ across the presence or absence of well-being programs. Thus, these results do not provide support for H3.

The full MATRIX can be found in Appendix C.

5. DISCUSSION

This study examined how the type of well-being intervention, AI-led versus HR-led, affects employee outcomes related to **s**tress**,** well-being**,** and perceived organizational support (POS)**.** Contrary to our expectations in Hypothesis 1, the type of intervention did not significantly influence either employee stress levels or well-being. Participants reported similar outcomes regardless of whether the intervention was delivered by AI or a human resource professional, suggesting that employees may evaluate intervention effectiveness more on perceived support than on the delivery agent alone.

Although no significant direct effect was found, Hypothesis 2 proposed that perceived organizational support would mediate the relationship between intervention type and well-being. Our findings indicate that POS strongly predicted both well-being and stress, but intervention type did not significantly influence POS, and the indirect effects were non-significant. This means that although POS is a strong predictor of employee outcomes, it was not significantly shaped by whether the intervention came from AI or HR in this study. This aligns with research noting that technological interventions often struggle to convey emotional cues essential for fostering trust (Strohmeier & Piazza, 2015; Tambe et al., 2019), yet in our case, those deficits may not have been strong enough to create statistically significant differences.

From the perspective of AI constraints (Valenzuela et al., 2024; Marimon & Mas-Machuca, 2024), this may reflect the challenge AI faces in expressing authentic organizational care, particularly in emotionally sensitive domains such as mental well-being. Although AI systems can personalize and scale support delivery, they may lack the relational depth that human-led interventions naturally provide (Huang et al., 2019).

Our findings offer partial support for Hypothesis 3, which tested whether organizational context, specifically the presence of formal well-being programs moderates the relationship between intervention type and POS. Results from the ANOVA showed a significant interaction: participants in organizations with existing well-being programs responded more favorably to AI-led interventions, perceiving them as part of a broader, consistent care strategy. However, the index of moderated mediation was not significant, suggesting that this interaction did not translate into a meaningful difference in the mediation pathway via POS. Thus, the moderating effect is best interpreted as contextually relevant but not sufficient to alter the overall mediation effect.

These findings highlight the importance of organizational readiness and cultural framing in shaping how AI-led interventions are received. In supportive contexts, AI may be interpreted more favorably; in their absence, the same tools may appear impersonal or insufficient. This indicates the need for organizations to embed technological interventions within a broader culture of care.

Finally, this study contributes to growing scholarship on the relational limits of AI in human-centric functions. From a Feeling Economy perspective (Huang et al., 2019), these results emphasize that the effectiveness of well-being initiatives lies not only in what they do but in how they make employees feel. Emotional authenticity, often conveyed through human interaction, remains critical to employee acceptance and psychological impact.

6. CONCLUSIONS AND FUTURE RESEARCH

This study offers new insights into how the design and delivery of organizational well-being interventions can shape employee psychological outcomes. Specifically, it examined the comparative effects of AI-led versus HR-led well-being initiatives on employee well-being, highlighting the mediating role of perceived organizational support (POS) and the moderating role of existing well-being programs. As AI becomes more embedded in HR practices, understanding not only whether it works, but how, for whom, and under what conditions is increasingly important.

6.1 THEORETICAL IMPLICATIONS

This research makes several theoretical contributions. First, it extends the literature on AI in human resource management by shifting focus from task automation to psychological support and care delivery. While much of the current scholarship emphasizes efficiency gains and predictive capabilities (Tambe et al., 2019), this study contributes to a growing conversation about the emotional and perceptual consequences of AI in employee-facing roles (Strohmeier & Piazza, 2015; Marimon & Mas-Machuca, 2024).

Second, the study integrates perceived organizational support (POS) into this discussion, showing that the source of an intervention (AI vs. human) significantly shapes how employees interpret organizational intent. This reinforces prior research highlighting POS as a key mechanism linking organizational behavior with employee outcomes (Rhoades & Eisenberger, 2002) and shows that AI-led tools may fall short if they do not evoke a sense of care.

Third, by incorporating organizational context as a moderator, specifically the presence or absence of formal well-being programs, this study highlights the crucial role of existing support structures in shaping how employees interpret and respond to interventions. The findings suggest that even well designed and scalable AI-led interventions are more likely to be perceived as authentic and supportive when introduced within a culture that already prioritizes employee well-being. In contrast, in environments lacking such programs, the same technologies may be met with skepticism or seen as impersonal. This insight contributes to the literature on technology acceptance and perceived organizational support by showing that the effectiveness of digital interventions depends not only on their functionality but also on the broader relational and cultural context in which they are deployed.

6.2 Practical and Managerial Implications

From a managerial perspective, the findings suggest that how well-being interventions are delivered matters just as much as what they deliver. HR professionals and organizational leaders should not assume that technology-based solutions are neutral or universally welcomed. Even when effective in reducing stress, AI-led interventions may be interpreted as less caring or authentic, particularly in organizations without a strong pre-existing support culture.

This implies that AI-driven systems must be implemented thoughtfully and ideally complemented by human-led practices. For example, combining automated stress detection with periodic human check-ins could help balance scale with empathy. Furthermore, organizations with well-established well-being programs are in a better position to introduce AI-led tools because employees are more likely to see them as enhancements rather than replacements.

The findings are also relevant for HR tech vendors and people analytics professionals. Building trust, transparency, and ethical use into AI design may be just as important as technical sophistication. Framing these tools as part of a broader care strategy, rather than as isolated digital solutions, can increase employee buy-in and perceived value.

6.3 Limitations and Future Research

While this study provides valuable contributions, it is not without limitations. First, the use of vignette-based scenarios, while well-suited for experimental control, may not fully capture the complexity of real-world workplace dynamics. Future studies could replicate the findings using field experiments or longitudinal data.

Second, our findings were based on a single sample in a specific cultural and professional context. Broader generalizability could be improved by replicating the study across industries, cultures, and roles, particularly those with high emotional labor demands.

Third, although the presence of well-being programs emerged as a significant contextual factor, our study only examined one moderator. Future research should explore other individual and organizational moderators, such as trust in AI, employee tech readiness, or organizational transparency.

Additionally, our operationalization of AI-led intervention may have lacked emotional nuance, potentially limiting its perceived authenticity. Incorporating more dynamic AI capabilities such as natural language processing, virtual coaching, or even emotionally expressive avatars could provide a more ecologically valid representation of future workplace AI.

Finally, there is an opportunity to explore hybrid models of support where AI tools are embedded within human-led frameworks, as a potential way to combine the strengths of both approaches. This may be especially important in global or hybrid workforces where scalability and empathy are both critical.

In conclusion, this study highlights the critical role of perceived organizational support and organizational context in shaping how employees respond to AI- and HR-led well-being interventions. As organizations increasingly embrace digital transformation in people management, balancing technological efficiency with emotional authenticity will be key to sustaining employee well-being.

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APPENDIX A

1. **Online Questionnaire in Qualtrics**

Block: Intro and Consent (1 Question)
BlockRandomizer: 1 - Evenly Present Elements
Block: Bots filter_2 (2 Questions) Block: Bots filter_3 (2 Questions) Block: Bots filter_4 (2 Questions) Block: Bots filter_5 (2 Questions) Block: Bots filter_6 (2 Questions)
BlockRandomizer: 1 - Evenly Present Elements
Block: HR-led (1 Question) Block: AI (1 Question)
Block: variables (2 Questions) Standard: mediator (1 Question) Block: Checks (3 Questions) Standard: Demographics (5 Questions) Block: Debriefing (1 Question)

Intro.
Dear participant,
This survey is being conducted as part of an academic research project at the NOVA Information Management School, in Lisbon, Portugal. Carefully read the provided scenario and answer the following questions. Remember that your participation in this survey is voluntary, which means that you are free to participate or not, as well as give up at any time. However, your responses are very important, completely anonymous, and will be used only for academic purposes. There is no risk involved in answering any of the questions.

Informed Consent Form I declare that I am 18 or over 18 and agree to participate in this research. I declare that I was informed that my participation in this study is voluntary and that I can leave this survey at any time without penalty, and all data is confidential. I understand that I will evaluate responses and that this study does not offer serious risks.

- o I agree to participate.
- o I do not agree to participate.

Scenario 1. Imagine yourself in the following situation**:** You have been experiencing moderate workplace stress for several weeks, affecting your ability to focus and perform at your best. Your organization recently introduced a traditional, HR-led well-being program. The HR department organizes weekly workshops, mindfulness training sessions, and group discussions focused on stress management and mental health awareness. These initiatives require your attendance at scheduled times and are manually coordinated by HR staff. Over the next few days, you participate in these HR-led programs and attend mindfulness workshops. You find the sessions helpful, and after engaging with these traditional interventions, you notice a decrease in your stress levels and an improvement in your overall well-being and productivity at work.

Scenario 2. Imagine yourself in the following situation**:** You have been experiencing moderate workplace stress for several weeks, affecting your ability to focus and perform at your best. Your organization recently implemented an AI-driven well-being system, designed to monitor employee stress levels and offer personalized recommendations. The AI system analyzes your daily interactions, workload, and stress patterns, and then proactively suggests personalized interventions such as mental health apps, virtual stress management coaching, and tailored mindfulness exercises. Over the next few days, the AI system sends timely reminders and personalized recommendations based on your stress patterns. You decide to try these AI-driven recommendations and find that your stress significantly decreases, improving your overall well-being and productivity at work.

Employee Stress Levels. Taking into account the scenario you read, to what extent do you agree with the following statements?

	1. Strongly disagree	2	3	4	5	6	7.Strongly agree)
I would often feel stressed at work	o	o	o	o	o	o	o
I would often feel over-whelmed by work-place de-mands	o	o	o	o	o	o	o
I would frequently experi-ence diffi-culties coping with my job re-sponsibili-ties	o	o	o	o	o	o	o
Work-place stress would negatively impacts my per-formance	o	o	o	o	o	o	o
Work-re-lated stress would negatively impacts my per-sonal life	o	o	o	o	o	o	o

Employee Well-Being. Taking into account the scenario you read, to what extent do you agree with the following statements?

	1. Strongly disagree	2	3	4	5	6	7.Strongly agree
At work, I would feel optimistic about my daily tasks	o	o	o	o	o	o	o
I would feel relaxed and calm during my working hours.	o	o	o	o	o	o	o
I would generally feel cheerful in my workplace	o	o	o	o	o	o	o
I would feel mentally healthy and focused during work	o	o	o	o	o	o	o
I would feel that my job positively contributes to my overall well-being	o	o	o	o	o	o	o

POS. Taking into account the scenario you read, to what extent do you agree with the following statements?

	1. Strongly disa-gree		3	4	5	6	7.Strongly agree
My organization would value my contributions to its well-being	o	o	o	o	o	o	o
My organization would care about my general satisfaction at work	o	o	o	o	o	o	o
My organization would show concern for me as a person	o	o	o	o	o	o	o
Help would be available from my organization when I have a problem	o	o	o	o	o	o	o
My organization would strongly consider my goals and values	o	o	o	o	o	o	o
My organization would take pride in my accomplishments at work	o	o	o	o	o	o	o

Scenario realism. The situation described in the scenario is...

- o 1. Unrealistic
- o 2
- o 3
- o 4
- o 5
- o 6
- o 7. Realistic

Manipulation & Attention. Taking into account the scenario you read, to what extent do you agree with the following statements?

	1. Strongly disagree	2	3	4	5	6	7. Strongly agree
The well-being intervention was manually managed by HR	o	o	o	o	o	o	o
The workplace intervention involved AI	o	o	o	o	o	o	o
To confirm your attention, please select option 3 for this question.	o	o	o	o	o	o	o

External. Has your organization implemented well-being or stress management programs?

- o Yes, it has.
- o No, it has not.

Age Age (in years)

____

Gender. Please indicate your gender.

- Male
- Female
- Other

Degree What is the highest level of education that you have completed?

- Less than high school diploma
- High school diploma
- Some university, but no degree
- Bachelor's Degree
- Master's Degree
- Doctorate

Income Which of the following best describes your monthly income?

- Less than 500 euros
- Between 501 and 1000 euros
- Between 1001 and 2000 euros
- Between 2001 and 3000 euros
- More than 3000 euros
- Prefer not to answer

Position Level Which of the following best describes your position level within your organization?

- Entry-level / Junior
- Intermediate-level
- Senior-level (non-managerial expert)
- Manager / Supervisor
- Senior Manager / Director
- Executive (VP, CEO, CFO, etc.)

2. Questionnaire Scale

Construct	Reference	Original Item	Adapted Item
Workplace Stress	Cohen et al. (1983)	1. I feel nervous or stressed at work 2. I find it hard to wind down after work due to demands 3. I feel difficulties relaxing because of work responsibilities 4. My job stress affects my ability to work well 5. Stress from work affects my life outside of work	1. I would often feel stressed at work 2. I would often feel overwhelmed by workplace demand 3. I would frequently experience difficulties coping with my job responsibilities 4. Work-related stress would negatively impact my personal life 5. Work-related stress would negatively impact my personal life
Employee Well-being	WHO-5 Well-being Index	1. I have felt cheerful and in good spirits 2. I have felt calm and relaxed 3. I have felt active and vigorous 4. I woke up feeling fresh and rested 5. My daily life has been filled with things that interest me	1. At work, I would feel optimistic about my daily tasks 2. I would feel relaxed and calm during my working hours 3. I would generally feel cheerful in my workplace 4. I would feel mentally healthy and focused during work 5. I would feel that my job positively contributes to my overall well-being
Perceived Organizational Support (POS)	Eisenberger et al. (1986); Rhoades & Eisenberger (2002)	1. My organization values my contribution to its goals 2. My organization cares about my satisfaction 3. My organization shows concern for me 4. If I need help, my organization will provide it 5. My organization takes my goals and values seriously 6. My organization is proud of my accomplishments	1. My organization would value my contributions to its well-being 2. My organization would care about my general satisfaction at work 3. My organization would show concern for me as a person 4. Help would be available from my organization when I have a problem 5. My organization would strongly consider my goals and values 6. My organization would take pride in my accomplishments at work

APPENDIX B

1. *Table of Internal Consistency of Scales*

Reliability Statistics

Cronbach's Alpha	N of Items
,91	5

Reliability Statistics

Cronbach's Alpha	N of Items
,86	5

Reliability Statistics

Cronbach's Alpha	N of Items
,94	6

2. *Table of Independent Samples t-Test for Manipulation Check Items*

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Taking into account the scenario you read, to what extent do you agree with the following statements? - The well-being intervention was manually managed by HR	Equal variances assumed	4,467	,036	5,105	173	<,001	<,001	1,257	,246	,771	1,743
	Equal variances not assumed			5,100	166,609	<,001	<,001	1,257	,246	,770	1,744
Taking into account the scenario you read, to what extent do you agree with the following statements? - The workplace intervention involved AI	Equal variances assumed	,914	,340	-5,397	173	<,001	<,001	-1,531	,284	-2,091	-,971
	Equal variances not assumed			-5,394	171,487	<,001	<,001	-1,531	,284	-2,091	-,971

3. *Table of Effect Sizes for Manipulation Check Items*

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Taking into account the scenario you read, to what extent do you agree with the following statements? - The well-being intervention was manually managed by HR	Cohen's d	1,629	,772	,464	1,078
	Hedges' correction	1,636	,769	,462	1,073
	Glass's delta	1,773	,709	,392	1,022
Taking into account the scenario you read, to what extent do you agree with the following statements? - The workplace intervention involved AI	Cohen's d	1,876	-,816	-1,123	-,506
	Hedges' correction	1,884	-,812	-1,119	-,504
	Glass's delta	1,952	-,784	-1,101	-,464

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

APPENDIX C

1. ESL and POS Mediation Effect

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : ESL
    X  : SCENARIO
    M  : POS

Sample
Size:  175

**************************************************************************
OUTCOME VARIABLE:
 POS

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0889      ,0079     1,8500     1,3770     1,0000   173,0000      ,2422

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,7470      ,3246    14,6247      ,0000     4,1063     5,3877
SCENARIO     -,2413      ,2056    -1,1735      ,2422     -,6472      ,1646

**************************************************************************
OUTCOME VARIABLE:
 ESL

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3304      ,1091     1,2743    10,5355     2,0000   172,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,3983      ,4029    13,4001      ,0000     4,6031     6,1935
SCENARIO      ,0523      ,1713      ,3055      ,7604     -,2859      ,3906
POS          -,2862      ,0631    -4,5349      ,0000     -,4107     -,1616


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0523      ,1713      ,3055      ,7604     -,2859      ,3906

Indirect effect(s) of X on Y:
```

```
         Effect     BootSE   BootLLCI   BootULCI
POS      ,0691      ,0634     -,0423      ,2122

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : ESL
    X  : SCENARIO
    M  : POS

Sample
Size:  175
```

```
OUTCOME VARIABLE:
 POS

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0889      ,0079     1,8500     1,3770     1,0000   173,0000      ,2422

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,7470      ,3246    14,6247      ,0000     4,1063     5,3877
SCENARIO     -,2413      ,2056    -1,1735      ,2422     -,6472      ,1646

**************************************************************************
OUTCOME VARIABLE:
 ESL

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3304      ,1091     1,2743    10,5355     2,0000   172,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
```

```
constant     5,3983      ,4029   13,4001      ,0000     4,6031     6,1935
SCENARIO      ,0523      ,1713     ,3055      ,7604     -,2859      ,3906
POS          -,2862      ,0631   -4,5349      ,0000     -,4107     -,1616


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0523      ,1713      ,3055      ,7604     -,2859      ,3906

Indirect effect(s) of X on Y:
        Effect     BootSE   BootLLCI   BootULCI
POS      ,0691      ,0654     -,0452      ,2146

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

2. EWB and POS Mediation Effect

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : ESL
    X  : SCENARIO
    M  : POS

Sample
Size:  175

**************************************************************************
OUTCOME VARIABLE:
 POS

Model Summary
          R       R-sq        MSE          F        df1        df2
      ,0889      ,0079     1,8500     1,3770     1,0000   173,0000      ,242

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,7470      ,3246    14,6247      ,0000     4,1063     5,3877
SCENARIO     -,2413      ,2056    -1,1735      ,2422     -,6472      ,1646

**************************************************************************
OUTCOME VARIABLE:
 ESL

Model Summary
          R       R-sq        MSE          F        df1        df2
      ,3304      ,1091     1,2743    10,5355     2,0000   172,0000      ,000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,3983      ,4029    13,4001      ,0000     4,6031     6,1935
SCENARIO      ,0523      ,1713      ,3055      ,7604     -,2859      ,3906
POS          -,2862      ,0631    -4,5349      ,0000     -,4107     -,1616


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0523      ,1713      ,3055      ,7604     -,2859      ,3906

Indirect effect(s) of X on Y:
```

```
        Effect     BootSE   BootLLCI   BootULCI
POS      ,0691      ,0634     -,0423      ,2122

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************
```

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : ESL
    X  : SCENARIO
    M  : POS

Sample
Size:  175

**************************************************************************
OUTCOME VARIABLE:
 POS

Model Summary
          R       R-sq        MSE          F        df1        df2         p
      ,0889      ,0079     1,8500     1,3770     1,0000   173,0000      ,242

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,7470      ,3246    14,6247      ,0000     4,1063     5,3877
SCENARIO     -,2413      ,2056    -1,1735      ,2422     -,6472      ,1646

**************************************************************************
OUTCOME VARIABLE:
 ESL

Model Summary
          R       R-sq        MSE          F        df1        df2         p
      ,3304      ,1091     1,2743    10,5355     2,0000   172,0000      ,000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,3983      ,4029    13,4001      ,0000     4,6031     6,1935
SCENARIO      ,0523      ,1713      ,3055      ,7604     -,2859      ,3906
POS          -,2862      ,0631    -4,5349      ,0000     -,4107     -,1616


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0523      ,1713      ,3055      ,7604     -,2859      ,3906

Indirect effect(s) of X on Y:
```

```
        Effect     BootSE   BootLLCI   BootULCI
POS      ,0691      ,0634     -,0423      ,2122

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : ESL
    X  : SCENARIO
    M  : POS

Sample
Size:  175

**************************************************************************
OUTCOME VARIABLE:
 POS

Model Summary
```

3. **Matrix Moderation Mediation Effect**

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 ***************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 7
    Y  : EWB
    X  : SCENARIO
    M  : POS
    W  : External

Sample
Size:  175

**************************************************************************
OUTCOME VARIABLE:
 POS

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1199      ,0144     1,8594      ,8319     3,0000   171,0000      ,4780

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,9058     1,0516     3,7143      ,0003     1,8301     5,9815
SCENARIO      ,3831      ,6571      ,5830      ,5606     -,9139     1,6801
External      ,5576      ,6532      ,8536      ,3945     -,7318     1,8470
Int_1        -,4173      ,4135    -1,0092      ,3143    -1,2336      ,3989

Product terms key:
 Int_1    :        SCENARIO x        External

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0059     1,0185     1,0000   171,0000      ,3143

**************************************************************************
OUTCOME VARIABLE:
 EWB

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6139      ,3768      ,9079    52,0079     2,0000   172,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,7794      ,3400     5,2329      ,0000     1,1082     2,4506
SCENARIO      ,0770      ,1446      ,5324      ,5952     -,2085      ,3625
```

```
Index of moderated mediation (difference between conditional indirect effects):
              Index     BootSE   BootLLCI   BootULCI
External     -,2265      ,2290     -,7023      ,2049

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

ANNEX

A. NOVA IMS Ethics Committee Approval

NOVA IMS Information Management School

This is to certify that

Project No.: **DDMKT2025-5-259289**

Project Title: **AI vs HR-Led Well-Being Interventions and Employee Well-Being: The Mediating Role of Perceived Organizational Support**

Principal Researcher: **Ioanna Novrouzai**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 5/25/2025.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 5/25/2025

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa