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Research paper

Beyond AI adoption: Psychological empowerment, work meaning, and employee well-being

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ABSTRACT

Introduction/Purpose: this study examines the associations between artificial intelligence use in workplace settings and employee well-being. It also considers work meaning and professional identity, perceived employment uncertainty linked to AI, and AI-related work demands, while addressing how psychological empowerment may influence employees' reactions to these technological changes.

Methodology: a quantitative. Cross-sectional approach was adopted. The study included 507 employees from six English-speaking countries, based on the AI, Work & Human Identity 2025 dataset developed by Human Clarity Institute (2025). The proposed relationships were examined using PLS-SEM to analyse the associations amongst the study variables and the corresponding mediation effects.

Results: the findings indicate that work meaning and identity, together with psychological empowerment related to AI use, were positively linked to employee well-being, while perceived job threat was negative association with well-being, psychological empowerment presented a partial mediating effect between work meaning and identity and employee well-being.

Conclusions: the findings suggest that the relationship between AI and employee well-being is influenced by specific psychological mechanisms.

Palabras clave:
Inteligencia artificial,
empoderamiento psicológico,
intensidad de trabajo,
amenaza percibida,
identidad percibida,
bienestar laboral

Más allá de la adopción de la IA: empoderamiento psicológico, significado del trabajo y bienestar de los empleados

RESUMEN

Introducción/objetivo: esta investigación analiza la inteligencia artificial (IA) y su relación con el bienestar de los empleados. Particularmente, examina el papel del significado e identidad del trabajo, la amenaza percibida al empleo y la intensificación del trabajo asociada con la IA, así como el papel mediador del empoderamiento psicológico en la respuesta de los trabajadores a esta tecnología.

Metodología: se adoptó un enfoque cuantitativo de corte transversal. La muestra fue de 507 empleados de seis países de habla inglesa, provenientes de la encuesta AI, Work & Human Identity desarrollado por el Human Clarity Institute (2025). Los datos fueron examinados mediante PLS-SEM para analizar las asociaciones entre las variables y los efectos de mediación.

Resultados: los hallazgos indican que el significado e identidad del trabajo, así como el empoderamiento psicológico ante el uso de IA, se relacionan de manera positiva y significativa con el bienestar de los empleados, mientras la amenaza percibida se relacionó de forma negativa con este. El empoderamiento psicológico media parcialmente la intensificación laboral con el bienestar, y entre la amenaza percibida y el bienestar. La intensificación de trabajo impulsada por IA no fue significativa

Conclusiones: se sugiere que la IA y sus efectos sobre el bienestar laboral son selectivos y mediados por procesos psicológicos, ofreciendo una comprensión más profunda del bienestar en contextos laborales mediados por IA.

Introduction

The growing adoption of artificial intelligence is changing organisational processes and contemporary work environments. Technical algorithms, automation, and machine learning are transforming activities, roles, and organisational processes across many industries, reinforcing the major trends of digital transformation and data-driven approaches (Kellogg et al.2020; Machucho & Ortiz, 2025).

Previous studies have highlighted productivity improvements based on digital technologies and AI-supported systems (Sánchez & De la Garza, 2018), their psychological implications regarding employee well-being remain less understood. Some studies suggest that technological change has influenced well-being indirectly through psychological and organisational factors, rather than through homogeneous direct associations (Kinowska & Sienkiewicz, 2023). AI adoption may be linked to well-being via identity-related perceptions, perceived job threats, and changes in job demands, though empirical evidence remains fragmented (Ortiz & Machucho, 2025; Sánchez et al., 2005).

Based on the job demands-resources (JD-R) theory (Bakker, 2013), an emerging line of research posits psychological empowerment as a key factor that impacts employees' perceptions of smart technologies (Ochoa & Coello, 2023; Spreitzer, 1995). Perceived control, fair recognition of performance, and psychological safety from the use of AI and assistive technologies have been shown to mitigate adverse effects and improve employee well-being (Passalacqua et al., 2025). However, empowerment appears to operate as a context dependent mechanism.

AI also reshapes the subjective experience of work, influencing perceptions of professional value, control, and well-being consistent with work identity theory (Ashforth et al., 2008; Kellogg et al., 2020; Passalacqua et al., 2025). Work meaning and identity (WMI) remain linked to employee well-being, though these associations are often incremental and context-dependent. Some authors point out that workers tend to report greater well-being when AI contributes to strengthening identity and work purpose (Patillon et al., 2026; Valtonen et al., 2025; Xu et al., 2025), although it is important to note that their contribution is modest because well-being is a multifactorial phenomenon (Teresi et al., 2024; Wegge et al., 2006).

On the other hand, incorporating AI can also generate fear of losing one's job, something that converges with the already existing fear of disuse of skills and loss of status (Sverke et al., 2002). Perceived job threat associated with AI tends to negatively affect employee well-being, although these effects are generally moderate when employees perceive opportunities for learning and adaptation.

These perceptions are negatively associated with employee well-being, although this is usually moderate (Byung & Min, 2024; Jin et al., 2024; Zheng & Zhang, 2025). Work practices such as transparency and continuous learning could help reduce these negative perceptions.

Psychological empowerment represents an important resource in AI-related work environments. It can be understood as a motivational state associated with meaning, competence autonomy, and perceived impact (Spreitzer, 1995; Zhang et al., 2025). This is expressed in AI-mediated environments as a perceived control effect on technology, AI-assisted performance recognition, and psychological safety. Some authors point out that empowerment is positively associated with well-being and suggest that it could mediate even partially the identity and perceptions related to the threat perceptions (Fan et al., 2023; Shi, 2024).

The incorporation of AI can also lead to an increase in work demands. AI-driven work intensification (AI-WI) refers to a faster pace of work, higher performance expectations, and long availability (Alsaad et al., 2025). While it has been linked to stress and burnout in some studies (Zheng & Zhang, 2025), it could also function as a challenge demand when employees have access to support resources, such as autonomy (Pienaar et al., 2025). Employee well-being (EWB) refers to that which includes different affective, cognitive, and energetic aspects of positive mental health at work (Bartels et al., 2019). It comes from the interactions between job demands, resources, and perceptions beyond technology (Claes et al., 2023).

Despite the boom that this topic has had, few studies have simultaneously examined work meaning and identity, the perceived threat to employment, work intensification, psychological empowerment and employee well-being. The present work is based on the theory of labour-resource demands (Bakker, 2013), identity theory in organisations (Ashforth et al., 2008), and the theory of psychological empowerment (Spreitzer, 1995), which aims to address the identified theorical gap. With data from employees from several English-speaking countries and PLS-SEM analyses, with particular attention to the mediating influence of psychological empowerment, Figure 1 proves the proposed associations between the variables considered in the study, including the influence of psychological empowerment.

In contrast to previous studies that tend to review isolated perceptions related to AI in the workplace, this study seeks to explore its parallel and associated relationships with employee well-being through a unified perception-based framework focused on psychological empowerment.

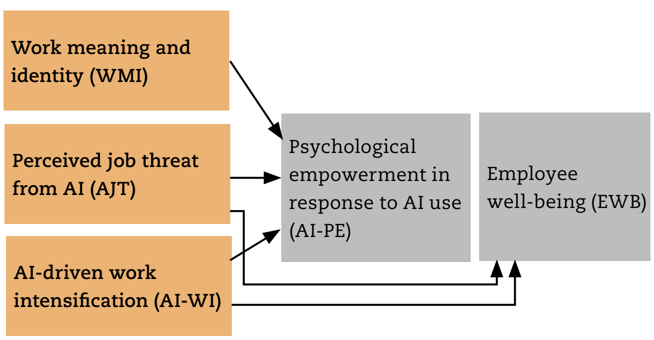

Figure 1. Theoretical framework of the proposed relationships

Source: Developed by the authors.

Methodology

Data

The information used in this study was obtained from the AI, Work & Human Identity 2025 dataset (Human Clarity Institute, 2025), designed, developed and documented by the Human Clarity Institute as part of its research programme on AI and Human Experience, which collected responses on November 12, 2025, by way of the Prolific platform. Participants were selected through a non-probability convenience sampling process involving employees from different English-speaking countries. Eligible participants were adults of legal age who were currently employed and capable of completing the questionnaire in English. The final sample consisted of 507 workers who reported some level of exposure to AI within their professional activities.

The dataset was considered appropriate for this study because it includes variables related to AI-based workplace perceptions, employees´ psychological experiences, and well-being, allowing the analysis of theoretically related constructs within the same organisational context.

The dataset was selected because it included multiple AI-related psychological and workplace perception variables theoretically aligned with the proposed model.

The instrument includes Likert-like scales ranging from 1–7, 0–10, and 1–5, along with categorical and open-ended questions. For this study, only items conceptually aligned with the proposed model were selected based on criteria of content validity and theoretical coherence, following the recommendations of Schames et al. (2024) and Weng (2024).

Five latent reflexive constructs were operationalised: work meaning and identity (WMI), which refers to employees´ sense of belonging within team, the perception of purpose at work, and the importance of work identity; perceived job threat from AI (AJT), that captures perceptions about job value, skills disuse, and stigma; psychological empowerment in response to the AI use (AI-PE), reflecting perceptions of control, fair recognition, and psychological safety; AI-driven work intensification (AI-WI), which refers to the perception of an increased work pace and heightened performance expectations; and employee well-being (EWB), assessed using the five items included in the WHO-5 Well-being Index.

The grouping of items in these constructs was justified theoretically and evaluated by the reflexive measurement model, maintaining theoretical alignment with the original conceptual framework. Due to the limitations inherent in using convenience sampling based on participants' self-reports at a single point in time, carefulness should be exercised when interpreting the results of this investigation, as they may not reflect all employees working in AI-related positions.

Therefore, the study adopts an exploratory perspective based on perception, focused on identifying statistical associations between psychological constructs related to AI, rather than establishing causal relationships. In addition, the sample included employees from different countries, professional backgrounds, economic sectors, and levels of exposure to AI. Therefore, the relationships identified in the model may vary across organisational and work contexts.

Future studies in Ai-related work environments could employ longitudinal or multigroup designs to further examine these different across contexts.

Study approach and scope

The study employed a quantitative approach aimed at examining the associations amongst latent psychological variables through statistical modelling techniques. It has an exploratory-correlational scope, which analyses the statistical relationships between employee perceptions. The study followed a cross-sectional and non-experimental approach, as the variables were examined without manipulation and the information was gathered during a single period of data collection, making it possible to observe statistical associations between AI-related perceptions and employee well-being.

The purpose of the investigation was not to establish cause-and-effect relationships, but to adequately analyse statistically significant associations between employees' perceptions of AI and their well-being at work. Since the sample included participants from different countries and occupations, the model was evaluated exploratively and from the perspective of perception, focusing on broader patterns of association rather than assuming full structural equivalence across groups.

Procedure

First, the dataset was extracted from the library of the Institute for Human Clarity (2025) and adapted to meet standards that allowed for its analysis. Before proceeding with structural modelling, the database design was analysed in SPSS v.21. Informed consent was verified, and the validity of the cases was determined, with no invalid cases found.

Descriptive statistics and response ranges were checked to ensure that the values remained within acceptable limits. Cases considered atypical at the univariate level will be identified through standardised scores above 3.29, whereas the detection of multivariate atypical cases will rely on Mahalanobis distance values. No manual data transformation or standardisation is performed, since the PLS-SEM model performs this process internally on the latent scores and is considered robust to deviations from normality (Hair et al., 2022).

Statistical analysis procedures

The analyses were conducted using partial least squares structural equation modelling (PLS-SEM) with SmartPLS 4.0, following the methodological guidelines outlined by Noreña (2024) and Hair et al. (2019, 2022). This method was deemed appropriate because the study falls within the scope of research focused on employees' perceptions of AI, as well as on the estimation of theoretical relationships between psychological constructs; Furthermore, PLS-SEM is considered a technique commonly used in organisational and behavioural research, which focuses on theoretical models and data from secondary surveys, and for which strict requirements for multivariate normality need not be assumed.

The analysis was organised into two stages. The initial stage focused on evaluating the adequacy of the measurement model by examining indicator reliability, internal consistency, convergent validity, and discriminant validity. The assessment also incorporated the analysis of outer loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), the Fornell–Larcker criterion, and the heterotrait–monotrait ratio (HTMT) (Hair et al. 2019; 2022; Noreña, 2024).

Afterwards, the evaluation focused on the structural model by examining collinearity through variance inflation factor (VIF) values and assessing the explanatory relevance of the proposed relationships using R^2, Q^2 predict, and effect size (f^2) indicators. Mediation effects were additionally explored through bootstrapping procedures (Hair et al. 2019; 2022; Noreña, 2024).

Mediation effects were tested using bootstrapping procedures with 10 000 resamples, bias-corrected and accelerated (BCa) confidence intervals, and a two-tailed significance criterion of .05, enabling the estimation of direct, indirect, and total effects within the proposed model (Hair et al. 2019; 2022; Noreña, 2024).

Ethical considerations

The following of international standards for research involving humans was verified, the informed consent of the survey participants was verified, being anonymous. Considering the use of a secondary database, there was no direct interaction with the respondents, so their confidentiality and privacy were preserved without having identification data of those who responded to the survey. The database is publicly accessible so transparency and replicability are guaranteed (Human Clarity Institute, 2025).

Results

Evaluation of indicator reliability and construct consistency

Indicator reliability and construct consistency were evaluated through the examination of outer loadings within the reflective measurement model. Following PLS-SEM recommendations, loadings equal to or greater than .708 were considered acceptable, whereas indicators with values between .40 and .708 were assessed according to their contribution to reliability and content validity (Hair et al., 2022; Noreña, 2024).

One indicator from the work meaning and identity construct (WMI) showing a negative loading was removed. WMI1 was removed from the model because it presented a negative loading, which could affect the internal consistency and reflective specification of the construct. While the documentation of the original dataset did not provide sufficient details to determine whether this result was associated with item wording, response interpretation, or conceptual ambiguity, retaining the indicator negatively impacted consistency and convergent validity. The remaining indicators continued to capture the core dimensions of work meaning and identity, associated with a sense of belonging and work purpose.

Constructs with two indicators were retained because the selected items represent the core conceptual dimensions of the original constructs and are theoretically aligned with the Human Clarity Institute framework. Given the reduced length in terms of construct definition and the potential loss of content coverage, the prior literature on PLS - SEM also acknowledges that constructs with only two items may be acceptable in cases where adequate support is found regarding conceptual consistency, reliability, and convergent validity (Eisinga et al., 2013; Hair et al., 2022).

The remaining indicators continued to highlight the core dimensions underlying the meaning and identity of work, which were linked to a sense of belonging and a sense of purpose in one's work, thus maintaining theoretical consistency with the original conceptual framework.

According to the construct of psychological empowerment in relation to AI, one of the indicators had an intermediate loading (0.502); however, it was retained because removing it did not improve either the reliability or the convergent validity (Hair et al., 2022; Noreña, 2024).

Construct consistency was examined through Cronbach's alpha and composite reliability indices (rho_A and rho_c), while convergent validity was assessed using the average variance extracted (AVE). Although Cronbach's alpha values for AJT (α = 0.667) and AI-PE (α = 0.687) were slightly below the conventional 0.70 threshold, the reliability measures recommended for PLS-SEM (rho_A and rho_c) exceeded this level, and AVE values were ≥ 0.50 for all constructs, which suggests acceptable convergent validity despite moderate internal consistency in some constructs (Dijkstra & Henseler, 2015; Hair et al., 2022; Noreña, 2024)

For AI-WI, the rho_A value above 1 may reflect a statistical artifact commonly associated with highly correlated two-item constructs in PLS-SEM. Nevertheless, this result indicates that the construct should be approached with caution and further reinforces the exploratory character of the study. For these situations, it is recommended to consider the validity of rho_c, AVE and content before removing elements (Dijkstra & Henseler, 2015; Eisinga et al., 2013). Despite this limitation, AI-WI showed acceptable rho_c and AVE values (rho_c >0.70; AVE = 0.78.

Overall, the measurement model suggests acceptable, albeit methodologically modest, levels of reliability and convergent validity for an exploratory perception-based study. A rho_A value greater than 1 may indicate a statistical artifact present in strongly related constructs of two elements, rather than a significant constraint of the instrument (Eisinga et al., 2013; Hair et al., 2022). Table 1 summarises the results obtained from the analysis.

Table 1. Assessment of construct consistency and convergent validity

Variable	Item	Outer loading	α	rho_A	rho_c	AVE
AJT	AJT1	.788	.667	.719	.817	.602
	AJT2	.877				
	AJT3	.646				
AI-PE	AI-PE1	.821	.687	.727	.812	.528
	AI-PE2	.834				
	AI-PE3	.700				
	AI-PE4	.502				
AI-WI	AI-WI1	.960	.749	1.069	.876	.780
	AI-WI2	.800				
WMI	WMI2	.919	.749	.773	.888	.798
	WMI3	.864				
EWB	EWB1	.881	.892	.899	.920	.698
	EWB2	.801				
	EWB3	.821				
	EWB4	.841				
	EWB5	.831				

Source: Developed by the authors.

Discriminant validity

Discriminant validity was examined to confirm that the constructs represented empirically distinguishable dimensions within the proposed model. According to the results presented in Table 2, the Fornell–Larcker criterion showed that the square root of the AVE for each construct was greater than the correlations with the remaining variables included in the analysis. Similarly, the HTMT values shown in Table 3 were below the conservative threshold of .85, indicating limited conceptual overlap among the constructs. Overall, these results provide support for the discriminant validity of the measurement model (Hair et al., 2019; Noreña, 2024).

Table 2. Fornell-Larcker Criterion

Variable	AJT	EWB	AI-PE	AI-WI	WMI
AJT	.776				
EWB	-.233	.835			
AI-PE	-.336	.397	.727		
AI-WI	.365	.135	.077	.883	
WMI	-.184	.446	.535	.141	.893

Source: Developed by the authors.

Table 3. HTMT ratio results

Variable	AJT	EWB	AI-PE	AI-WI	WMI
AJT					
EWB	.272				
AI-PE	.523	.514			
AI-WI	.561	.164	.303		
WMI	.230	.538	.729	.197	

Source: Developed by the authors.

Structural model evaluation

The structural model in PLS-SEM enables the assessment of the theoretical relationships among the study constructs once the validity and reliability of the measurement model have been established (Hair et al., 2019; Noreña, 2024). At this stage, collinearity among predictor constructs, the significance and relevance of path coefficients, as well as the predictive capacity and statistical relevance of the proposed model are examined.

Assessment of collinearity issues in the structural model

Before evaluating the structural model and conducting the mediation analysis, collinearity among the predictor constructs was assessed. Evaluating collinearity is an important step in PLS-SEM because high levels of collinearity may influence the estimation and stability of the path coefficients (Hair et al., 2019).

Following recent methodological recommendations, the variance inflation factor (VIF) was used, calculated based on the latent variable scores of the predictor constructs in each regression of the structural model (Hair et al., 2022; Sarstedt et al., 2019). Table 4 indicates that all VIF values remained below the recommended threshold of 3, suggesting that collinearity did not constitute a significant concern and supporting the interpretation of the path coefficients and mediation effects within the proposed model.

Furthermore, because all primary constructs were assessed using self-reported responses collected from the same participants during a single stage of data collection, the potential presence of common method bias (CMB) cannot be entirely dismissed. Following methodological recommendations for PLS-SEM research, procedural precautions associated with the original survey design included anonymity, standardised item presentation, and integrated quality control procedures. Additionally, the VIF values obtained remained below the conservative threshold commonly associated with potential common method variance problems (Kock, 2015). Nevertheless, the findings should be interpreted with caution due to the cross-sectional nature of the data and the reliance on perception-based measures.

Table 4. Variance inflation factor (VIF)

Relationship	VIF
AJT -> EWB	1.368
AJT -> AI-PE	1.234
AI-PE -> EWB	1.553
AI-WI -> EWB	1.238
AI-WI -> AI-PE	1.216
WMI -> EWB	1.427
WMI -> AI-PE	1.091

Source: Developed by the authors.

Significance and relevance of structural model relationships

The significance of the path coefficients was analysed by non-parametric bootstrapping with 10 000 subsamples, using BCa confidence intervals and a significance level $\alpha = 0.05$, according to the recommendations for the PLS-SEM approach (Hair et al., 2019; Noreña, 2024).

As presented in Table 5, the perceived job threat from AI (AJT) is negatively and significantly related to both employee well-being (EWB) and psychological empowerment in response to AI (AI-PE). On the other hand, work meaning and identity (WMI) maintains positive and significant relationships with both variables, positioning itself as the strongest predictor in the model within the analysed model. Likewise, the AI-PE shows a positive relationship with employee well-being, while the AI-driven work intensification (AI-WI) does not show significant direct effects.

Considering that the study analyses variables related to perceptions and psychological processes, the effect sizes must be assessed within the context of this type of phenomenon. In psychological research, it is common to find relationships of small or moderate magnitude, which can continue to provide relevant evidence from a theoretical point of view (Gignac & Szodorai, 2016; Schäfer & Schwarz, 2019). Consequently, the coefficients obtained in the model remain within expected values and consistent with what has been reported in studies with similar characteristics.

Table 5. Path coefficients: Significant and non-significant relationships

Relationship	Original sample	Sample mean	Standard deviation	T Statistics	P values
AJT -> EWB	-.173	-.176	.047	3.711	.000
AJT -> AI-PE	-.293	-.288	.042	6.936	.000
AI-PE -> EWB	.164	.169	.054	3.033	.002
AI-WI -> EWB	.143	.136	.086	1.654	.098
AI-WI -> AI-PE	.118	.108	.063	1.874	.061
WMI -> EWB	.306	.306	.046	6.606	.000
WMI -> AI-PE	.465	.467	.039	12.043	.000

Source: Developed by the authors.

Coefficient of determination (R^2)

The explanatory power of the model was evaluated through the coefficient of determination (R^2). The results presented in Table 6 indicate that the model accounted for 26.2% of the variance in EWB and 35.6% of the variance in AI-PE.

Based on widely accepted criteria in PLS-SEM and social sciences research, these values reflect weak to moderate levels of variance accounted for by the model, which are considered acceptable for the analysis of complex and multifactorial psychological phenomena (Noreña, 2024).

Table 6. R^2 Coefficient

Variable	R2
EWB	.262
AI-PE	.356

Source: Developed by the authors.

Predictive relevance (Q^2)

A Q^2 prediction procedure was conducted to assess predictive relevance where the values obtained were 0.342 for AI-PE and 0.229 for EWB, which indicates that the model has a predictive utility beyond the data used for estimation (Hair et al., 2019; Noreña, 2024). A greater predictive contribution of AI-PE can be observed; this difference may be associated with the complexity and variability typically present in psychological constructs related to employee well-being.

Table 7. Q^2 predict values

Variable	Q^2predict
AI-PE	.342
EWB	.229

Source: Developed by the authors.

Effect size (f^2) of predictor constructs

The magnitude of structural effects was examined through the f^2 statistics, which estimates the relative contribution of each predictor construct to the explained variance of the endogenous constructs (Hair et al., 2019).

As shown in Table 8, WMI exhibited the strongest effect among the relationships included in the model, with effect sizes ranging from moderate to high for AI-PE and from small to moderate for EWB. Additionally, AJT suggests a small to moderate effect on AI-PE and a small effect on EWB, whereas AI-WI shows small or negligible associations on both endogenous constructs.

Table 8. Effect size (f^2)

Relationship	Original sample	Sample mean	Standard deviation	t Statistics	p values
AJT -> EWB	.030	.034	.017	1.737	.082
AJT -> AI-PE	.108	.110	.034	3.160	.002
AI-PE -> EWB	.024	.027	.017	1.420	.156
AI-WI -> EWB	.022	.029	.019	1.169	.242
AI-WI -> AI-PE	.018	.021	.017	1.063	.288
WMI -> EWB	.089	.092	.029	3.051	.002
WMI -> AI-PE	.308	.320	.068	4.526	< .001

Source: Developed by the authors.

Overall, the results of the structural model suggest acceptable empirical consistency and theoretical coherence, with no collinearity issues, significant structural relationships, and acceptable predictive relevance and statistical consistency. The findings emphasise the significant contribution of WMI and AI-PE in explaining employee well-being (EWB), whereas AI-WI does not demonstrate significant direct associations, consistent with the multifactorial nature of the psychological processes analysed.

Once the evaluation criteria for both the reflective measurement model and the structural model have been met, it is appropriate to proceed with the mediation analysis of the proposed model (Noreña, 2024).

Mediation analysis

A mediation analysis was conducted to examine whether psychological empowerment in response to AI use (AI-PE) transmits the associations of AI-related perceptions on employee well-being (EWB) (Hair et al., 2019; 2022; Noreña, 2024). The analysis evaluated the significance of indirect associations and compared direct, indirect, and total effects.

The results suggest the mediating role of AI-PE. Significant indirect associations were found for work meaning and identity (WMI → AI-PE → EWB; $\beta = 0.076$, $p = 0.005$) and perceived job threat from AI (AJT → AI-PE → EWB; $\beta = -0.048$, $p = 0.005$). In both cases, direct associations remained significant, indicating complementary partial mediation.

In contrast, no significant indirect effect of AI-driven work intensification (AI-WI) on EWB through AI-PE was observed, indicating the absence of mediation. The results are reported in Table 9.

Table 9. Presentation on the mediating effect

Type of effect	Relationship	Path coefficient (β)	t Statistics	p values
Tot. eff.	WMI → EWB	.382	8.214	.000
Tot. eff.	AJT → EWB	-.221	4.965	.000
Dir. eff,	WMI → EWB	.306	6.606	.000
Dir. eff.	AJT → EWB	-.173	3.711	.000
Indir. eff.	WMI → AI-PE → EWB	.076	2.797	.005
Indir. eff.	AJT → AI-PE → EWB	-.048	2.837	.005

Source: Developed by the authors.

Discussion

The purpose of this study was to examine how psychological processes associated with AI adoption (WMI, AIT, AI-PE, and AI-WI) relate to employee well-being (EWB). Overall, the findings suggest that AI-related job perceptions are associated with variation in employees´ self-reported well-being primarily through selective psychological processes rather than direct technological associations (Kellogg et al., 2020; Parker & Grote, 2022; Valtonen et al., 2025).

This study was not intended to evaluate the technical performance of AI systems themselves, but rather to examine how employees interpret and psychologically experience AI-related perceptions in the workplace and how these perceptions are associated with well-being.

Work meaning and identity shows a positive and significant relationship with the EWB, consistent with previous research linking meaningful work and work meaning and identity to employee well-being (Oerlemans & Bakker, 2018). Even so, the moderate effect should be considered. This reflects how, in AI-mediated contexts, work meaning and identity remains relevant even if it is not a central determinant of well-being. In highly digitised contexts, work meaning and identity still appears to function as a source of psychological stability and adaptation to technological change (Cuesta-Valiño et al., 2026, Salazar-Altamirano et al., 2026; Villanueva et al., 2026).

Perceived job threat associated with AI shows a negative and significant association with EWB, which is in line with what has been found in studies suggesting that technological insecurity is linked to lower levels of psychological well-being (Byung & Min, 2024; Zheng & Zhang, 2025). The relatively small effect suggests that AI-related job threat from AI functions as a moderate psychological stressor rather than a dominant determinant (Jansen et al., 2025; Xu et al., 2023). Organisational support and learning opportunities may help reduce the negative effects of AI-related job insecurity on employee well-being (Lin, 2026; Montero et al., 2025; Tsai, 2022).

Psychological empowerment with respect to the use of AI is positively associated, consistent with research linking empowerment to employee well-being in digitised contexts (Marin & Bonavia, 2021; Valtonen et al., 2025). However, this may reflect the fact that empowerment operates as a complementary resource (Kellogg et al., 2020; Parker & Grote, 2022).

Mediation analysis suggests that psychological empowerment may be a predictor of the statistical relationships found between work meaning and identity, and that job threat may be a predictor of emotional well-being, thereby supporting the view that psychological mechanisms mediate these relationships in a selective manner (Parker & Grote, 2022).

From a practical standpoint, the results indicate that organisations implementing AI technologies should consider adopting complementary technologies, such as systems that promote autonomy, participation, ongoing training, and open communication amongst managers and employees, during digital transformation processes; conversely, the intensification of work driven by AI does not show statistically significant associations with worker well-being in the analytical model of this study, which may suggest that the effects of AI-driven work intensification vary depending on the context of implementation and do not lead to negative perceptions of worker well-being across all work environments.

However, AI-mediated work intensification does not show any statistically significant association with worker well-being in the proposed model, suggesting that the effects of AI-mediated work intensification are dependent on the organisational context and do not necessarily lead to negative perceptions of well-being in different work environments.

Although intensification has previously been linked to a decline in well-being (Albor, 2022), this interpretation is also consistent with research that distinguishes between demands that are burdensome and those that are challenging (Chen et al., 2021; Galanakis & Tsitouri, 2022; Kim et al., 2023). Sometimes, in certain organisational contexts, work intensity and the subjective meanings derived from it are perceived as a manageable challenge or are mitigated through support strategies, work-life balance, and digital adaptation (González-González et al., 2026; Xia, 2021).

Not all workers associate the intensification of work under AI with a negative effect, and this is especially true when they believe that AI systems contribute to efficiency, the management of appropriate tasks, and the ability to adapt professionally, rather than increasing work intensity, adding pressure, or making work more controlling. All these findings suggest that psychological empowerment does not act as a mediator between work intensification under AI and its effect on the employee (EWB), insofar as work intensification may operate more closely with the view of work as an instrumental condition rather than as a psychological mechanism.

Workplace perceptions related to AI have an impact on workers' well-being, more through selective psychological processes than through direct technological effects. Therefore, the results should be understood as associations based on perceptions derived from cross-sectional self-reported data, rather than as evidence of causal psychological associations that determine the adoption of AI. Overall, the associations examined were minimal, which is also consistent with the exploratory nature of the research.

It is also worth noting that all variables were collected from the same participants at a single point in time, so the possible influence of common bias cannot be completely ruled out. The results of this study suggest that employee well-being depends less on the implementation of AI than on how employees perceive and interpret AI-related changes in the workplace, particularly those related to perceived threats and psychological control.

The findings of this study suggest that workers' well-being is not so much linked to the adoption of artificial intelligence (AI) per se—which could be viewed more as a set of administrative practices—but rather to how workers interpret the workplace changes brought about by AI, particularly changes that affect their perception of threats and psychological control.

On the other hand, it is also worth considering that, despite the sample's great occupational, sectoral, and geographic heterogeneity, the observed associations could all vary depending on the organisational context and levels of exposure to AI, such that these results cannot be interpreted as evidence of universal relationships to which all work contexts affected by AI might be exposed. Likewise, this pattern could also reflect the fact that work experiences related to AI are not shaped by normative standards, whether negative or positive, but rather through psychological interpretations that, depending on organisational contexts, could be influenced by meaning, perceived control, and the perception of professional significance.

Conclusions

This study examined the association between AI adoption and employee well-being (EWB) through key psychological mechanisms. The findings indicate that work meaning and identity (WMI) and AI-related psychological empowerment (AI-PE) are positively linked to EWB, whereas perceived job threat derived from AI (AIT) is negatively associated with employee well-being. In contrast, no empirical evidence was found for the direct or indirect influence of AI-driven work intensification (AI-WI) (AI-WI). Overall, the observed associations were modest, indirect, and dependent on contextual and psychological factors associated with AI use.

Theoretically, this study shows AI acting as a sociotechnical context that shapes psychological resources rather than directly dictating employee well-being. Psychological empowerment partially mediates links between constructs such as work meaning and identity, identity, and perceived jobs threats from AI on one side, and well-being on the other, but not so much for AI driven work intensity. Overall, the findings indicate that employee well-being is influenced more by employees' psychological interpretations of AI-related transformations than by increases in workload alone.

From a practical point of view, the evidence suggests that organisations should prioritise strategies that strengthen work meaning and identity, reducing perceived threats to employment by AI and organisations should prioritise strategies aimed strengthening psychological empowerment, establishing conditions that stimulate autonomy, fair recognition of AI-assisted performance and psychological safety could facilitate a better adaptation to AI in work environments. Also, organisations could benefit from observing their employees' perceptions of the stress, uncertainty, and role changes associated with AI during implementation.

Actions that organisations can take can include involving employees in AI implementation processes, offering opportunities for continuous training, being clear about the complementary role of AI in job tasks, and promoting transparent communication about technology changes and expectations for performance.

In the social context, the findings indicate that employee well-being in AI-mediated environments is shaped more strongly by organisational narratives and socially constructed interpretations than by the technology itself. Narratives emphasising job displacement may reinforce perceptions of threat and negatively affect employee well-being, highlighting the importance of policies that encourage continuous learning, employee involvement, and the preservation of meaningful work.

This research presents several limitations associated with its cross-sectional approach and reliance on self-reported information, which restrict the examination of causal relationships among the variables and may introduce common method bias. In addition, because the sample included employees in various national, occupational, sectoral, or AI-exposed contexts, associations could vary depending on where they are organisationally and professionally, so the findings should not be interpreted as universal in AI-mediated work environments.

Also, as a limitation can be seen in the constructs that were represented by a limited number of indicators, which could limit the coverage or stability of the construct, despite showing reliability and reliable and valid convergent metrics.

Future research could consider employing longitudinal and multilevel designs, as well as other cultural contexts in their replication, for an analysis of the temporal evolution and contextual variability of the psychological effects on the perception of AI on employee well-being.

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Conflict of interest declaration

The authors report no conflicts of interest related to this study.

Declaration of the use of generative artificial intelligence (AI) and AI-assisted technologies

The authors declare that they did not use generative artificial intelligence tools or AI-assisted technologies in the writing, development, analysis, image generation, or preparation of this manuscript.

Author's contribution

Mónica Lorena Sánchez Limón: Conceptualisation, Methodology, Formal Analysis, Supervision, Project Administration, Writing – Original Draft, Writing – Review & Editing; David Josué Ortiz González: Investigation, Data Curation, Validation, Software, Formal Analysis, Visualisation, Writing – Review & Editing; Julio César Castañón Rodríguez: Conceptualisation, Resources, Supervision, Visualisation, Validation, Writing – Review & Editing.

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