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Work-Life Balance, Technology-Enabled Work, and Workplace Happiness: A Machine-Learning Typology of Manufacturing Workers in Mexicali, Mexico

Mayda Alejandra Calderon Diaz

mayda.calderon@essex.ac.uk

University of Essex

Alex Sandra Gutierrez Macias

Universidad Autónoma de Baja California

Diana Oliveros Contreras

Universidad Autónoma de Bucaramanga-UNAB

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Abstract

This study investigates work-life balance workers of manufacturing microenterprises in Mexicali, Baja California, Mexico. Using data from 347 workers, we combine classical psychometric and regression analyses with supervised and unsupervised machine-learning techniques. The results show that organizational WLB culture and positive spillover are substantially more important predictors of workplace happiness than AI-related technology exposure itself. The Random Forest model achieved an out-of-fold AUC of 0.837 and an accuracy of 73%, with organizational WLB culture emerging as the strongest predictor. Importantly, the clustering analysis identified four distinct worker profiles: Thriving Digital, Strained and Hyperconnected, Traditional Low-Tech Balanced, and Disengaged and Unsupported. Workers in the Thriving Digital profile combined high levels of AI-related technology engagement with strong WLB conditions and exhibited the highest levels of happiness and performance. By contrast, workers in the Strained and Hyperconnected profile reported similarly high technological engagement but greater work-life interference and comparatively lower well-being outcomes. The results indicate that the relationship between AI-related technology and workplace well-being varies across organizational conditions. Workers with similar levels of technology engagement reported different levels of well-being depending on their work-life balance conditions in a manufacturing context in Mexicali, Mexico.

1. Introduction

During the 19th century, industrialization significantly affected family life. Workers now had to work in places different from the home, and women could no longer contribute to production the way they did when working from home (Olsen, 1983; Kleinberg, 1989). In the 20th century, the concept of work-life balance became relevant again, driven by the emergence of movements such as the women's liberation movement. These movements promoted policies and initiatives that would allow women to reconcile their work life with their family life, especially in the case of working mothers (Brough et al., 2008; Raja and Stein, 2014).

In the 20th century, the concept of work-life balance was understood as the compatibility between work and personal roles, such that the person could feel satisfied with the performance of both (Greenhaus and Beutell, 1985; Frone et al., 1992). Now, in the 21st century, work-life balance is understood as the appropriate and voluntary distribution of resources to meet the requirements of both roles. This allows workers to feel satisfied on both fronts, and their work and personal lives to progressively improve (Fisher, 2001; Fleetwood, 2007; Hayman, 2005).

In recent decades, research on work-life balance and happiness has increased, since both constructs have been shown to have a positive impact on individuals. However, it is worth noting that, while studies and findings exist on workplace happiness and work-life balance individually, further research is needed into the relationship between both constructs, even more so considering that there is empirical evidence suggesting indications of such an association (Fisher, 2001; Hayman, 2005; Cannas et al., 2019; Diener et al., 1999; Seligman, 2002; González et al., 2018; Bataineh, 2019).

According to Medrano (2014), people's happiness constitutes the foundation for achieving success, fulfilling goals, and satisfying personal expectations. Therefore, interest in personal happiness has extended beyond the individual dimension to encompass experiences in the workplace (Fisher, 2010). Consequently, it is essential to address those factors that have an impact on workers' happiness in the workplace context, not only to analyze job performance but also to enable workers to experience physical, mental, and emotional balance, which naturally leads to an improved quality of life (Parada, 2018).

Recently, of well-being have employed artificial intelligence and machine learning techniques. For instance, authors such as Rossouw and Greyling (2026) used XGBoost and SHAP to determine the relationship between well-being indicators and behavioral outcomes. Building on this emerging literature, the present study applies supervised and unsupervised machine learning techniques to examine workplace happiness in relation to work-life balance and AI-related workplace technology experiences. In this study, we test this concept among workers in the manufacturing sector in Mexicali. To this end, we

formulated the following research question: How are work-life balance conditions and AI-related workplace technology experiences associated with workplace happiness among manufacturing workers in Mexicali, Mexico?

2. Literature Review

2.1 Workplace Happiness and Well-Being

Happiness has historically been conceptualized as a form of subjective well-being that individuals experience in relation to their own lives (Diener et al., 1999). This concept can be understood through two dimensions. The first is the hedonic component, which encompasses positive affect, while the second is the eudaimonic component, which is intrinsically related to individuals' sense of purpose and the fulfilment of their potential (Seligman, 2002). Workplace happiness, therefore, refers to the extent to which individuals experience positive cognitive and affective evaluations of their work experience (Fisher, 2010).

However, happiness is not limited to positive experiences in the workplace. According to Medrano (2014), happiness extends beyond the occupational domain, as it is also experienced when individuals pursue success, fulfil their personal expectations, and achieve their life goals. Parada (2018), in turn, argues that workplace happiness is important not only for assessing productivity, but also for enabling workers to experience physical, mental, and emotional balance. Similarly, González et al. (2018) report that workers with higher levels of workplace happiness are less likely to express intentions to leave their jobs.

Nevertheless, workplace happiness differs significantly between men and women (Bataineh, 2019), particularly due to gender gaps in household and caregiving responsibilities. Inflexible working conditions and persistent gendered expectations regarding domestic responsibilities mean that women workers are disproportionately affected by the demands of balancing paid employment with household and caregiving duties.

2.2 Conceptual Evolution of Work-Life Balance

The concept of work-life balance (WLB) has evolved since its emergence. Authors such as Greenhaus and Beutell (1985) and Frone et al. (1992) understood this concept as the compatibility between personal and work life, which are differentiated by distinct roles and obligations. From this perspective, role conflicts may naturally arise, particularly in relation to time and the tensions associated with fulfilling different roles.

By the 2000s, Fisher (2001) and Hayman (2005) defined WLB as the appropriate and voluntary allocation of resources, such as time, energy, and attention, across different life domains. When resources are allocated in this way, individuals may be better able to manage the two spheres of their lives in a more positive manner. Therefore, an imbalance in the voluntariness of resource allocation does not necessarily reflect only an excess of objective demands but may also indicate a lack of autonomy to choose how to fulfil either work-related or personal roles. Factors such as individual autonomy, income, and trust are positively associated with gender equality and life satisfaction (Graafland & Schilpzand, 2025).

From an enrichment perspective, experiences in one life domain can generate resources that improve functioning and quality of life in another domain (Greenhaus & Powell, 2006). Additionally, Fleetwood (2007) argues that WLB can be achieved more voluntarily when individuals have greater flexibility in their working schedules, particularly in relation to household responsibilities, which are socially and disproportionately associated with women.

2.3 The Gender Dimension of Work-life Balance

Authors such as Olsen (1983) and Kleinberg (1989) have examined the separation between domestic and paid work following the Industrial Revolution. They argue that industrialization physically separated the workplace from the home, reducing women's ability to combine paid employment with domestic responsibilities. It was not until the mid-twentieth

century that policies specifically aimed at facilitating the reconciliation of work and family responsibilities for women began to emerge (Brough et al., 2008; Raja and Stein, 2014).

Nevertheless, although structural barriers have diminished in many contexts, a gender gap persists in the way family and work-related resources are negotiated within the household (Greenhaus and Beutell, 1985). The unequal distribution of domestic responsibilities can limit women's access to night shifts and flexible work arrangements, as they continue to undertake a "second shift" within the household as part of the gendered division of domestic labour. Similarly, authors such as Althammer, Wöhrmann, and Michel (2025) found that flexible work arrangements may facilitate the allocation of resources across work and personal domains; however, they do not necessarily guarantee a balance between the two, particularly for women.

Giménez-Nadal et al., (2023) demonstrate that there are gender differences in subjective well-being. Their research shows that the time devoted to paid and unpaid activities differs between men and women: women spend more time on unpaid work and childcare, whereas men devote more time to paid employment. These findings reinforce the premise that the distribution of domestic and care work is shaped by gender. These constraints may restrict women's access to employment conditions that are frequently associated with higher remuneration and career advancement, particularly in manufacturing contexts (Del Rio-Lozano et al., 2025).

Finally, Cannas et al. (2019) and Bataineh (2019) found that there is a positive relationship between individuals who report a satisfactory work-life balance and lower levels of stress and higher levels of happiness. Likewise, this positive relationship functions as an antecedent to workplace happiness, given that the depletion of personal resources leads to lower subjective well-being at work. Employees whose perception of WLB is higher show greater levels of engagement and personal satisfaction, two components closely related to workplace happiness.

However, the aforementioned authors agree that in manufacturing sectors, especially in emerging countries where informality is much more concentrated, this relationship tends to be weaker or more difficult to achieve. Likewise, domestic work for women is more rigid, and institutional support tends to be lower (Clark, 2000; Fleetwood, 2007).

Therefore, if WLB is achieved through the voluntary distribution of resources (Fisher, 2001; Hayman, 2005), and if the distribution of resources is conditioned by gender (Greenhaus and Beutell, 1985), then the literature gap identified in this research suggests that the intensity and nature of the relationship between WLB and happiness may differ between men and women.

2.4 Artificial Intelligence, Technology and Workplace Well-being

Regarding the relationship between artificial intelligence, technology, and well-being in the workplace, authors such as Valtonen et al. (2025) found, in a sample of more than 207 workers, that AI adoption does not have a direct influence on workers' well-being, but rather operates indirectly through job security and task optimization.

On the other hand, Pinho et al. (2026) found, in a sample of 280 workers, that AI positively predicts both work engagement and work-life balance. However, they argue that artificial intelligence can be an essential tool for human interaction that influences employee well-being, beyond performance outcomes.

It is precisely the use of technology and artificial intelligence that has enabled work contexts to change, as in the case of hybrid work. Authors such as Marks et al. (2026) explain that technology can contribute to two things: the intensification of work, as in the case of job demands, and the extension of work, or the reinforcement of overwork and the blurring of boundaries between work and personal life. As a result, Marks et al. (2026) found that digital connectivity can contribute to work-life conflict, which affects employee well-being.

This is precisely what Chuang et al. (2025) found in their research. Using Bayesian models, they found that AI has a double edge at work. On one hand, generative AI and effective AI tools can boost productivity and job satisfaction, but on the other

hand, AI-related stress can make people feel more drained and create conflicts between work and family life. Basically, AI's impact on how employees feel isn't always the same for everyone.

3. Methodology

3.1 Research Design and Context

This study adopts a quantitative, non-experimental, cross-sectional research design. The empirical setting is the manufacturing sector in Mexicali, Baja California, Mexico, an industrial context in which work organization may involve relatively structured schedules and differentiated operational and administrative positions. The study focuses on subordinate paid workers employed in manufacturing microenterprises.

We examine incorporate workplace happiness, job performance, and two dimensions of AI- and technology-related work experience: technology-driven hyperconnection and AI-enabled time facilitation. Our aim is to analyse the relationship between technology and workplace happiness is homogeneous or instead depends on the broader work-life balance environment.

A total of 363 questionnaires were collected between August 15 and November 28, 2024. Sixteen observations in which respondents selected “prefer not to say” for gender were excluded from the gender-comparative dataset in the original study. The resulting analytical sample used in the present re-analysis comprises 347 workers: 213 men (61.4%) and 134 women (38.6%). Of these respondents, 218 (62.8%) occupied operational positions and 129 (37.2%) occupied administrative positions (Table 1).

Table 1
Sample characteristics

Characteristic	n	%
Total	347	100.0
Men	213	61.383
Women	134	38.617
Operational role	218	62.824
Administrative role	129	37.176
Source: own elaboration		

3.2 Measurement Instrument

Data were collected using a structured self-administered questionnaire. The original instrument was developed from established work-life balance measures, particularly Fisher (2001), Hayman (2005), and Nitzsche et al. (2014), and was subjected to expert content validation using Aiken’s V and a pilot test involving 36 workers. The original questionnaire was reduced from 32 to 30 substantive work-life balance items following assessment of item redundancy and clarity.

All substantive constructs were measured using five-point Likert scales ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). For the present analysis, items belonging to each dimension were averaged to generate composite scores. Higher scores indicate greater levels of the construct, except for the two interference dimensions, for which higher scores indicate greater work-life or life-work interference. The re-analysis distinguishes four dimensions of work-life balance:

Work-to-life interference (ITV)

The extent to which work demands interfere with personal life.

Life-to-work interference (IVT)

The extent to which personal or family demands interfere with work.

Positive spillover/perceived improvement (PM)

The extent to which experiences in one domain contribute positively to the other.

Organizational work-life balance culture (CB)

The extent to which the organization supports and promotes work-life balance.

These dimensions were retained separately because they capture conceptually different aspects of the work-life interface and demonstrated strong internal consistency in the re-analysis.

Workplace happiness was operationalized through three dimensions: job satisfaction (SL), work engagement (CI), and affective commitment (CA). The three dimensions were combined to create an overall workplace happiness score. Job performance was similarly represented through task performance (DT) and contextual/adaptive performance (DC).

Finally, two technology-related dimensions were incorporated into the analysis: Technology-driven hyperconnection (THC), reflecting persistent or intensified connectivity associated with workplace technologies. AI-enabled time facilitation (FOT), reflecting the perceived capacity of AI-related technologies to facilitate or save time in work activities.

These two dimensions were developed specifically for the present study and therefore require more cautious interpretation than the established scales. THC demonstrated acceptable internal consistency (α = 0.700), whereas FOT showed relatively weak internal consistency (α = 0.541).

3.3 Reliability of the Measures

In the main constructs, the measurement scales demonstrated high internal consistency. Cronbach's alpha coefficients were 0.935 for job satisfaction, 0.933 for work engagement, and 0.931 for affective commitment, with an overall coefficient of 0.859 for happiness at work. Likewise, the two performance dimensions also showed high reliability, with α = 0.937 for task performance and α = 0.927 for contextual/adaptive performance, while the coefficient for the overall performance construct was α = 0.864. Similarly, the four work-life balance dimensions showed high internal consistency, with α = 0.940 for work interference with personal life, α = 0.951 for personal life interference with work, α = 0.902 for positive spillover, and α = 0.921 for organizational WLB culture. In contrast, AI-enabled time facilitation (α = 0.541) showed lower reliability. Consequently, we consider that findings involving FOT are interpreted cautiously rather than treated as definitive evidence of the absence or presence of an AI effect (Table 2).

Table 2
Reliability and descriptive statistics

Construct	Components	M	SD	α
SL	9	3.748	0.951	0.935
CI	13	3.690	0.847	0.933
CA	7	3.314	1.130	0.931
DT	8	3.984	0.893	0.937
DC	8	3.913	0.930	0.927
ITV	9	2.783	1.105	0.940
IVT	7	2.465	1.177	0.951
PM	7	3.359	1.008	0.902
CB	7	3.288	1.081	0.921
THC	5	3.267	0.911	0.700
FOT	5	3.215	0.828	0.541
Workplace happiness (SL/CI/CA)	3	3.584	0.868	0.859
Performance (DT/DC)	2	3.948	0.856	0.864
Source: own elaboration				

3.4 Analytical Strategy

The analysis proceeded in four stages. First, descriptive statistics and zero-order correlations were calculated to characterize the distribution of the principal constructs and their bivariate relationships.

Second, hierarchical ordinary least squares (OLS) regression was conducted with workplace happiness as the dependent variable. Demographic and employment controls were entered first, followed by the four WLB dimensions, and finally the two technology-related dimensions. This model provided a classical statistical benchmark against which the machine-learning results could subsequently be evaluated.

Third, supervised machine-learning models were estimated to assess the predictive contribution of the variables to workplace happiness. Because the objective was classification rather than continuous prediction, overall happiness was dichotomized at the sample median (3.63), producing 174 observations in the high-happiness group and 173 in the low-happiness group. Logistic Regression was used as a linear benchmark, while Random Forest and Gradient Boosting were used to capture potentially nonlinear relationships. All models were evaluated using stratified five-fold cross-validation. Model performance was assessed using out-of-fold AUC, accuracy, and F1 score.

For interpretability, Random Forest feature importance and TreeSHAP values were examined. SHAP values quantify the contribution of individual predictors to model predictions and therefore provide an interpretable assessment of which dimensions are most strongly associated with the classification of workers into high- versus low-happiness groups.

Fourth, an unsupervised K-means clustering procedure was applied to the standardized WLB and technology dimensions: ITV, IVT, PM, CB, THC, and FOT. The purpose was not to predict happiness but to identify naturally occurring combinations of work-life balance and technology experiences. The optimal number of clusters was selected using silhouette scores for solutions ranging from two to six clusters. The four-cluster solution produced the highest silhouette score (0.223).

We used regression, supervised machine learning, explainable AI, and unsupervised clustering makes it possible to examine both the overall predictive structure of workplace happiness and the heterogeneity of workers' experiences.

4. Results

4.1 Descriptive Statistics

The mean overall workplace happiness score was 3.58 (SD = 0.87), while overall performance had a mean of 3.95 (SD = 0.86). Mean work-to-life interference was 2.78 (SD = 1.10), and mean life-to-work interference was 2.47 (SD = 1.18). Positive spillover had a mean of 3.36 (SD = 1.01), and organizational WLB culture had a mean of 3.29 (SD = 1.08).

The mean level of technology-driven hyperconnection was 3.27 (SD = 0.91), while AI-enabled time facilitation had a mean of 3.21 (SD = 0.83). The FOT scale should be interpreted cautiously because its internal consistency is low (α = 0.541).

Table 3 presents the correlation structure. It provides an initial indication that workplace happiness is more strongly associated with organizational and work-related conditions than with AI-related technology exposure. Happiness correlated moderately with positive spillover (r = 0.45) and organizational WLB culture (r = 0.55), and more strongly with overall performance (r = 0.65). By contrast, its correlations with work-to-life and life-to-work interference were weak and negative (approximately r = − 0.11). Importantly, happiness was essentially unrelated to technology-driven hyperconnection (r = 0.10) and AI-enabled time facilitation (r = 0.03).

Table 3
Correlations with workplace happiness

Variable	r
Performance	0.650
ITV	-0.106
IVT	-0.108
PM	0.449
CB	0.547
THC	0.098
FOT	0.035
age	0.147
tenure	0.205
Source: Own elaboration	

4.2 Hierarchical Regression

The hierarchical OLS analysis provides a first test of the relative contribution of demographic, WLB, and technology-related variables.

The initial model containing age, tenure, gender, occupational role, and ordinal income explained 5.9% of the variance in workplace happiness ($R^2 = 0.059$). Adding the four WLB dimensions increased explained variance to 37.0%, corresponding to $\Delta R^2 = 0.310$ ($p < .001$). Adding technology-driven hyperconnection and AI-enabled time facilitation increased R^2 only marginally to 0.372, with $\Delta R^2 = 0.002$. The final regression used 347 complete cases (Table 4).

Table 4
Full-model OLS coefficients with HC3 robust SE

Predictor	B	HC3 SE	Std. β	t	p	VIF
age	0.003	0.005	0.032	0.503	0.615	1.613
tenure	0.021	0.011	0.117	1.944	0.053	1.610
gender_male	-0.010	0.080	-0.005	-0.122	0.903	1.111
role2	0.102	0.083	0.057	1.220	0.223	1.203
income_ord	0.009	0.068	0.008	0.127	0.899	1.172
ITV	-0.064	0.055	-0.081	-1.163	0.246	2.584
IVT	-0.080	0.049	-0.109	-1.632	0.104	2.575
PM	0.172	0.066	0.200	2.594	0.010	1.912
CB	0.325	0.062	0.404	5.242	0.000	1.856
THC	0.045	0.047	0.048	0.968	0.334	1.050
FOT	0.011	0.052	0.011	0.211	0.833	1.056
Note: Model 1 R^2 = 0.059; Model 2 R^2 = 0.370; Model 3 R^2 = 0.372. Maximum VIF = 2.58. The Breusch–Pagan test was significant (p < .001), motivating HC3 robust standard errors.						
Source: Own elaboration						

In the full model, organizational WLB culture was positively associated with workplace happiness (B = 0.325, HC3-robust p < .001), followed by positive spillover (B = 0.172, HC3-robust p = 0.010). Technology-driven hyperconnection (B = 0.045, HC3-robust p = 0.334) and AI-enabled time facilitation (B = 0.011, HC3-robust p = 0.833) were not significant. Gender and occupational role were also not significant.

These results suggest that the organizational and relational context surrounding work-life balance contributes substantially more to workplace happiness than exposure to AI-related technologies considered independently.

4.3 Gender as a Robustness Analysis

Welch's t-tests using the raw responses found no statistically significant gender differences in overall happiness, overall performance, or any WLB dimension. The largest absolute effect size was small (|d| < 0.13). For example, Table 5 presents the the gender difference in workplace happiness was d = − 0.05 (p = 0.643), and the difference in organizational WLB culture was d = − 0.08 (p = 0.447).

Table 5
Gender robustness analysis

Variable	Men M	Women M	Welch t	p	Cohen d
Happiness	3.565	3.614	-0.522	0.602	-0.057
Performance	3.940	3.961	-0.223	0.824	-0.024
ITV	2.792	2.767	0.212	0.832	0.023
IVT	2.429	2.523	-0.745	0.457	-0.081
PM	3.336	3.397	-0.550	0.583	-0.060
CB	3.244	3.358	-0.975	0.330	-0.106
THC	3.266	3.269	-0.030	0.976	-0.003
FOT	3.174	3.279	-1.169	0.244	-0.126
Source: own elaboration					

4.4 Supervised Machine-Learning Results

Three classification algorithms were compared using stratified five-fold cross-validation on the 340 complete cases. Logistic Regression, Random Forest, and Gradient Boosting produced broadly similar predictive performance. The Random Forest had the highest mean AUC in the reproducible analysis (Table 6).

Table 6
Supervised machine-learning performance

Model	AUC mean	AUC SD	Accuracy	F1	Precision	Recall
Logistic regression	0.831	0.042	0.755	0.756	0.759	0.758
Random Forest	0.837	0.031	0.735	0.730	0.739	0.729
Gradient Boosting	0.808	0.027	0.703	0.699	0.715	0.689
Source: own elaboration						

The similarity between the three models is noteworthy. The results do not indicate that workplace happiness classification depends on highly complex nonlinear structures that are detectable only by flexible machine-learning algorithms. Instead, the predictive structure appears to be broadly consistent with the monotonic and additive relationships observed in the classical regression analysis.

The Random Forest model used 500 trees, maximum depth five, and minimum leaf size eight. The classification exercise is treated as secondary because workplace happiness is fundamentally a continuous construct. This analysis avoids relying exclusively on a median split of workplace happiness (Table 7).

Table 7
Continuous-happiness sensitivity analysis

Model	CV R^2	MAE	RMSE
Random Forest regressor	0.492	0.470	0.608
Gradient Boosting regressor	0.430	0.488	0.646

Source: own elaboration

4.5 Feature Importance and Explainable Machine Learning

The Random Forest and SHAP analyses produced highly convergent results. Organizational WLB culture was the most important feature in the Random Forest (0.260), followed by contextual/adaptive performance (0.208), positive spillover (0.150), and task performance (0.114). Work-to-life interference contributed .060 to Random Forest importance and 0.025 in mean absolute SHAP terms, with a negative direction. Life-to-work interference contributed 0.045 and 0.014, respectively, and also showed a negative but weaker association. Technology-driven hyperconnection and AI-enabled time facilitation had comparatively small Random Forest importance values (0.025 and 0.021, respectively), while gender had an importance of 0.004 (Table 8).

Table 8
Random Forest feature importance

Feature	Importance
CB	0.260
DC	0.208
PM	0.150
DT	0.114
ITV	0.061
IVT	0.046
age	0.043
tenure	0.042
THC	0.025
FOT	0.021
income_ord	0.018
role2	0.008
gender_male	0.004

Source: own elaboration

The Random Forest and SHAP results showed a similar pattern. Organizational WLB culture and positive spillover had substantially greater contributions than the two AI-related measures. Organizational WLB culture and positive spillover emerge as substantially more important than the two AI-related dimensions. The combined importance of THC and FOT is below 5%, whereas culture, spillover, and performance account for approximately 60% of total feature importance.

Thus, the machine-learning analysis does not reveal a hidden direct AI effect that was absent from the regression model. Instead, it reinforces the conclusion that the organizational work-life balance environment is central to workplace happiness.

4.6 A Machine-Learning Typology of Worker Well-Being

The K-means analysis identified four profiles among 347 workers with complete data for the clustering variables. The results of this test present that the four-cluster solution achieved the highest silhouette score (0.222) among k = 2–6 (Table 9). Due to separation is modest, the clusters are interpreted as exploratory empirical profiles rather than fixed worker types.

Table 9
K-means profiles

Profile	n	%	ITV	IVT	PM	CB	THC	FOT	Happiness	Performance
Strained and Hyperconnected	122	35.159	3.787	3.603	3.656	3.511	3.641	3.303	3.566	3.791
Disengaged and Unsupported	78	22.478	2.246	1.888	2.103	2.033	3.097	3.190	3.065	3.583
Traditional Low-Tech Balanced	92	26.513	1.830	1.416	3.828	3.893	3.607	3.663	3.988	4.358
Thriving Digital	55	15.850	2.909	2.514	3.701	3.564	2.109	2.305	3.683	4.132

Source: own elaboration

4.6.1 Profile 1: Strained and Hyperconnected

The largest group comprised 123 workers (36.2%). These workers reported high levels of work-to-life interference (3.75) and life-to-work interference (3.58), alongside relatively high technology-driven hyperconnection (3.61) and AI-enabled time facilitation (3.34). Organizational WLB culture was comparatively high (3.51), but not as high as among the Thriving Digital group.

Their mean happiness was 3.56 and mean performance was 3.79. Thus, high technology engagement did not automatically translate into high well-being when technological connectivity coexisted with substantial interference between work and personal life.

4.6.2 Profile 2: Disengaged and Unsupported

This group consisted of 75 workers (22.1%) and displayed low levels of both work-life interference and positive spillover. Organizational WLB culture was the weakest of the four profiles (2.02). Technology engagement was moderate rather than high, with THC = 3.14 and FOT = 3.15.

Despite relatively low interference, this group had the lowest happiness score (3.09) and the lowest performance score (3.62). This pattern indicates that the absence of technological hyperconnection is not sufficient to generate positive well-being when workers perceive weak organizational support for WLB.

4.6.3 Profile 3: Traditional Low-Tech Balanced

The Traditional Low-Tech Balanced profile comprised 55 workers (16.2%). These workers reported relatively low levels of technology engagement (THC = 2.11; FOT = 2.31), but comparatively strong positive spillover (3.70) and organizational WLB culture (3.56).

Their mean happiness was 3.68 and their mean performance was 4.13. This profile demonstrates that high technology engagement is not a necessary condition for positive workplace outcomes when organizational and work-life balance conditions are supportive.

4.6.4 Profile 4: Thriving Digital

The Thriving Digital profile comprised 87 workers (25.6%). It was characterized by the lowest levels of work-to-life interference (1.82) and life-to-work interference (1.39), combined with the highest positive spillover (3.84) and organizational WLB culture (3.87). At the same time, workers reported high technology-driven hyperconnection (3.63) and AI-enabled time facilitation (3.66).

This group reported the highest workplace happiness (3.99) and performance (4.36) of all four profiles. Table 10 presents ANOVA tests indicated significant differences among the four profiles in both workplace happiness ($F = 17.35$, $p < .001$) and performance ($F = 14.78$, $p < .001$). Cluster membership was not significantly associated with gender ($\chi^2 = .52$, $p = .913$) or occupational role ($\chi^2 = 3.53$, $p = .317$).

Table 10
Cluster differences in happiness, performance, gender and occupational role

Test	Variable	Statistic	df	p
One-way ANOVA	Workplace happiness	$F = 17.35$	3, 343	< .001
One-way ANOVA	Performance	$F = 14.78$	3, 343	< .001
Chi-square	Gender	$\chi^2 = 0.52$	3	.913
Chi-square	Occupational role	$\chi^2 = 3.53$	3	.317

Note: ANOVA degrees of freedom reflect four cluster profiles ($k - 1 = 3$) and 347 cases ($N - k = 343$). Chi-square tests assess the association between cluster membership and gender or occupational role.

Source: Own elaboration

5. Discussion

The central finding of this study is that AI-related workplace technology does not exhibit a uniform relationship with workplace happiness. Instead, the well-being implications of technological engagement appear to depend on the organizational work-life balance conditions in which technology is embedded.

This conclusion emerges consistently across the three analytical approaches. First, the hierarchical regression demonstrates that the addition of WLB dimensions produces a substantial increase in explained variance in workplace happiness, whereas adding the AI-related dimensions produces almost no additional explanatory power. Second, the supervised machine-learning models reproduce this pattern: organizational WLB culture is the strongest feature, while THC and FOT make negligible contributions. Third, the clustering analysis demonstrates that workers with similarly high technology engagement can experience markedly different levels of happiness depending on their levels of interference, positive spillover, and organizational support.

5.1 Organizational Context Matters More Than Technology Exposure Alone

The strongest predictor of workplace happiness in both the regression and machine-learning analyses is organizational WLB culture. This finding reinforces the conceptualization of WLB as more than an individual capacity to allocate time between work and personal life. The organizational environment shapes the extent to which workers can exercise autonomy over these competing domains.

The importance of organizational WLB culture is particularly relevant in the context of technological transformation. Digital connectivity may increase employees' capacity to communicate, coordinate, and complete tasks, but these potential benefits do not necessarily translate into greater well-being. When connectivity expands without corresponding organizational support, it may intensify work-life interference.

It's important to mention that the two worker profiles show different patterns despite their high levels of technological participation. The Digital Prosper group reported less interference between work and personal life and a higher WLB culture compared to the Stressed and Hyperconnected group.

Both groups report high technological engagement. However, the Thriving Digital group experiences substantially lower work-life interference, stronger organizational WLB culture, higher positive spillover, and considerably higher happiness and performance. Thus, the relevant question is not simply whether workers use AI-related technologies, but under what organizational conditions they use them.

5.2 Low Technology Exposure Is Not Sufficient for Well-Being

The Disengaged and Unsupported profile provides an equally important counterpoint. These workers report relatively low technology engagement and low levels of work-life interference, yet they experience the lowest happiness and performance.

This finding demonstrates why the relationship between technology and well-being should not be interpreted through a simple “more technology versus less technology” framework. Reduced technological exposure does not necessarily create well-being. Workers may avoid hyperconnection but still experience low happiness if they lack organizational support, positive spillover, and a culture conducive to work-life balance.

The Traditional Low-Tech Balanced profile reinforces this point from another direction: workers can experience relatively favorable happiness and performance despite low technology engagement when their organizational WLB conditions are strong. Together, these profiles indicate that technology intensity and workplace well-being are distinct dimensions rather than opposite ends of a single continuum.

5.3 Performance and Happiness Are Closely Interconnected

Job performance was another major predictor of workplace happiness. Contextual/adaptive performance and task performance ranked immediately after organizational WLB culture and positive spillover in the machine-learning feature-importance analysis.

The relationship should nevertheless be interpreted as associative rather than causal. Because the data are cross-sectional and based on self-reported measures, the present study cannot establish whether better performance increases happiness, whether happier workers perform better, or whether both are influenced by shared organizational conditions.

The result is nevertheless theoretically relevant because it suggests that workplace happiness is embedded within a broader system of organizational functioning rather than being an isolated employee attitude.

5.3 No Significant Differences by Gender

In this study, no differences were found in work-life balance, technology-enabled work, or workplace happiness by gender. We consider this an indicator that the organizational and technological conditions experienced by workers play a more substantial role in shaping these outcomes than gender alone. Future research could examine whether gender interacts with other factors, such as occupational role, caregiving responsibilities, hours of caregiving, organizational position, or access to technological resources.

6. Limitations and Future Research

The observed associations do not allow us to determine whether organizational WLB culture generates higher levels of happiness, or whether happier workers perceive their organizations more positively. Likewise, the questionnaires were administered in paper-and-pencil format and were based on self-report; therefore, the presence of common method variance cannot be ruled out. Additionally, the sample is restricted to workers in small manufacturing companies in Mexicali, Baja California, so the results should not be generalized to other occupational contexts. Finally, although technology-driven hyperconnection showed acceptable internal consistency ($\alpha = 0.700$), AI-enabled time facilitation showed a relatively low reliability coefficient ($\alpha = 0.541$). Consequently, the weak contribution of AI-enabled time facilitation (AITF) is not definitive evidence that AI-enabled time facilitation is unrelated to happiness. We believe that future research

could replicate these findings using longitudinal and multi-source data to analyze AI-related work experiences and to examine whether organizational culture and work-life balance influence well-being and happiness, with an ethnic and gender focus.

7. Conclusions

We conclude that work-life balance conditions matter substantially more than exposure to technology. The study was conducted with 347 manufacturing workers in Mexicali, Mexico. By combining regression with supervised machine learning, SHAP-based explainability, and unsupervised clustering, we found that organizational WLB culture and positive spillover were the strongest predictors of workplace happiness, whereas technology-driven hyperconnection and AI-enabled time facilitation contributed very little to predictive performance.

Among the findings of this study, we identified four worker profiles: Strained and Hyperconnected, Disengaged and Unsupported, Traditional Low-Tech Balanced, and Thriving Digital. The coexistence of high-technology workers with both high and low well-being demonstrates that AI-related technological engagement does not have a uniform consequence.

Likewise, comparing the Thriving Digital and Strained and Hyperconnected profiles suggests that technology may function as an amplifier of organizational conditions. This is relevant because it means that high technology engagement is compatible with high happiness and performance when workers also experience low interference, positive spillover, and strong organizational WLB culture. Similarly, the same level of technological engagement can be associated with substantially poorer outcomes when work-life interference is high.

Additionally, the Traditional Low-Tech Balanced and Disengaged and Unsupported profiles show that low technological engagement is neither inherently protective nor detrimental. The factor that distinguishes between these groups is the organizational and work-life context surrounding technology use.

In particular, we also showed that gender and occupational roles among manufacturing workers in Mexicali, Mexico did not explain the main patterns identified by the full-scale analyses, and cluster membership was not associated with gender or occupational position. This suggests that worker well-being profiles may cut across conventional demographic categories and that organizational conditions may be more informative than demographic labels when identifying heterogeneous experiences of technologically mediated work. Well-being-oriented digital transformation requires organizational environments that allow technological tools to enhance work.

Declarations

Author Contribution

MACD: Conceptualization, methodology, statistical analysis, data curation, design and verification, writing-review and editing, original draft preparation.ASGM: Conceptualization, methodology, statistical analysis, writing-review and editing, original draft preparation.DOC: Supervision, writing-review and editing.

Data Availability

The data used in this study were collected through questionnaires administered to manufacturing workers in Mexicali, Baja California, Mexico, between August 15 and November 28, 2024. The final analytical sample consisted of 347 participants. Data may be made available from the corresponding author.

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