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Comparing predictive validity of additive versus multiplicative AMO models to explain attitudinal outcomes of job satisfaction

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Abstract

Purpose: This study examines the impact of human resources management (HRM) systems on attitudinal outcomes in Spain, comparing the predictive capacity of two alternative individual-level models (additive and multiplicative) with a focus on job satisfaction.

Design/methodology/approach: The analysis draws on data from the Spanish sample of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC). Partial least squares regression (PLS) is applied, along with complementary tests of observed and unobserved heterogeneity and out-of-sample predictive power.

Findings: The models account for up to 10% of the variance in job satisfaction across the whole sample. Ability-enhancing practices have the greatest effect, followed by opportunity-related practices, while motivation contributes minimally. The multiplicative model performs slightly better than the additive one, revealing significant interaction effects among ability, motivation, and opportunity, the practical relevance of which should be further examined in future research. The explanatory power increases slightly when focusing on managerial employees. Accounting for unobserved heterogeneity identifies five employee segments, for which the multiplicative model achieves R^2 values ranging from 0.42 to 0.76.

Research limitations/implications: PIAAC is a secondary, cross-sectional dataset, which limits analytical flexibility and prevents causal inference.

Practical implications: Understanding how AMO dimensions interact may help HR managers design more effective practice configurations to foster job satisfaction.

Originality/value: Empirical comparisons between additive and multiplicative applications of the AMO model remain scarce. Most prior research focuses on extrinsic motivation practices (such as pay-for-performance) and shows weak links with job satisfaction, while intrinsic motivation is rarely addressed. This study contributes to closing that gap and identifies five employee groups that differ in how they weigh the factors driving job satisfaction.

Keywords: Job satisfaction, Ability, Motivation, Opportunities, Human resource management

JEL codes: M50, O15

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1. Introduction

Employee participation encompasses management practices that involve employees in sharing information and making decisions. It has become essential to organisational success, as it enables firms to meaningfully improve results (Bos-Nehles et al., 2023; Huselid, 1995; Juarez-Tarraga et al., 2019). High-performance work programs (HPWP) (also referred to as high-involvement or innovative work systems) (Bayo-Moriones & Galdon-Sanchez, 2010), constitute a set of HRM practices designed to make organisations more participative, flexible, and competitive.

Previous research suggests that exploring the influence of the mediating path between HRM and organisational outcomes (distal outcomes) by integrating proximal outcomes (e.g., employee attitudes like job satisfaction) may provide a more integrative model of how HRM systems influence distal outcomes (Escribá-Carda et al., 2023; Gil et al., 2025; Guest, 1997; Huang, 2025; Katou, 2017). According to social exchange theory, the resource-based view, and the expectancy theory of motivation, HPWP can increase job satisfaction and employee engagement, likely improving firm performance (Bryson & White, 2019; Prentice, 2022).

The Ability-Motivation-Opportunity (AMO) framework is widely used to explain the link between HRM practices and performance (Marín-García & Martinez-Tomas, 2016). According to the AMO model, there are three dimensions: skill requirements, jobs designed to use those skills, and an incentive structure to induce discretionary effort (Appelbaum et al., 2000). However, there is no consensus on how these practices should be combined, additively or multiplicatively (Boon et al., 2019; Bos-Nehles et al., 2023; Dasí et al., 2021; Marín-García & Martinez-Tomas, 2016). Nonetheless, since most studies have used the additive approach (Boon et al., 2019), it remains unclear whether the multiplicative approach better explains the interaction among AMO bundles.

We aim to contribute to the HRM debate by examining which approach better explains how HRM practices should be combined to account for their effects on individual job satisfaction. Most studies apply an additive approach, while only a few explore a multiplicative one, despite its closer alignment with the original AMO model. To compare the two perspectives, we employ partial least squares regression (PLS) to assess their predictive validity in explaining attitudinal outcomes.

The paper is structured as follows: first, we present the theoretical framework, focused on job satisfaction, AMO-enhancing practices, and alternative ways of combining HRM practices. Second, we describe the methodology, outlining the sample, variables, and statistical procedures. We draw on data from the International Assessment of Adult Competencies (PIAAC), which includes employee perceptions on items relevant to our study. Third, we present the results, and finally, we summarise the main conclusions and propose future research directions.

2. Theoretical Framework

Job satisfaction can be defined as a person's overall evaluation of their job or its different aspects (Meier & Spector, 2015). There are two main approaches for measuring job satisfaction (Christen et al., 2006). The first approach measures overall job satisfaction by asking respondents about their general feelings towards the job (Martins & Proença, 2014). The second approach measures job satisfaction by assessing an individual's satisfaction with various facets of the job (Adiguzel et al., 2020; Martinez-Tomas & Cuevas-Lopez, 2026). An example of this second approach is the Minnesota Satisfaction Questionnaire (MSQ), a 5-point Likert scale that measures 20 work features (Weiss et al., 1967). The job facets approach is likely to yield a deeper understanding of the subject (Martins & Proença, 2014). However, most research focuses on the global level of job satisfaction

(Meier & Spector, 2015). Some studies indicate that, under certain conditions, the global approach may be more effective than the facet approach (Tett & Meyer, 1993).

Several factors consistently correlate with job satisfaction (Sypniewska et al., 2023). They can be categorised as individual, job, or organisational factors (Al-Doghan et al., 2019). At the personal level, personality traits, age, and seniority, among others, vary from one employee to another and may play an important role (Al-Doghan et al., 2019). At the job level, work variety, autonomy, or simply having a challenging job may play an essential role as moderators (Bastida et al., 2022). Likewise, cooperative workgroups, high levels of participation, supportive supervisors, and friendly interpersonal relationships can foster job satisfaction (Adiguzel et al., 2020; de-Juana-Espinosa & Rakowska, 2018; Huang, 2025; Sypniewska et al., 2023). At the organisational level, company fair policies, leadership behaviour, salaries, intrinsic or extrinsic rewards, and changes in promotion policies are likely to influence job satisfaction (Bonavia & Marin-Garcia, 2019; Prentice, 2022). In this regard, HRM practices are significantly related to employee job satisfaction (Marín-García et al., 2011; Rapp et al., 2025).

HRM research has widely utilised the ability-motivation-opportunity (AMO) model (Appelbaum et al., 2000; Bailey, 1993) to study the relationship between HRM and performance (Beltrán-Martín & Bou-Llusar, 2018; Marín-García & Martinez-Tomas, 2016). The model's premise is that effective HRM drives positive discretionary behaviours associated with working beyond basic requirements (McGrath, 2024; Purcell et al., 2003). Discretionary effort, in turn, will positively affect organisational outcomes. The model states that employee performance occurs when people possess the appropriate skills for the job requirements, are willing to perform, and organisations provide them with opportunities to develop their capacities (Boselie, 2010; Boxall & Purcell, 2003; Marín-García, 2013).

The ability dimension (A) refers to the employees' capacities to perform their tasks (Jiang et al., 2013). Ability-enhancing practices ensure employees acquire the appropriate knowledge, skills, and abilities (Alba et al., 2021; Bryson & White, 2019). These practices include formal training, rigorous selection, comprehensive recruitment and development, and performance assessment techniques to ensure that employees gain the necessary skills to fulfil their job requirements (Kroon et al., 2013). Training and development HRM practices increase the likelihood of developing new skills, discovering new opportunities, understanding complex problems, and engaging in socialisation processes (Tian et al., 2016). Some authors argue that the impact of ability-enhancing practices will be greater in jobs with higher skill demands (Subramony, 2009) or for line managers than for frontline workers (Bayo-Moriones & Bello-Pindado, 2021). Line managers require skills across a variety of domains, including planning, coordination, supervision, problem-solving, information management, negotiation, and leadership (Bayo-Moriones & Bello-Pindado, 2021; Beltrán-Martín & Bou-Llusar, 2018; Bonavia & Marin-Garcia, 2019; Subramony, 2009).

Motivation (M) refers to the internal factors that initiate and maintain a particular behaviour or discretionary effort (Bayo-Moriones & Bello-Pindado, 2021; Jiang et al., 2013). Self-determination theory distinguishes between extrinsic and intrinsic motivation. Some authors argue that extrinsic rewards focus on short-term gains, whereas intrinsic motivation connects with long-term commitment (Schimansky, 2014). Motivation-enhancing practices are designed to encourage employees to feel more job satisfaction and perform beyond the basic requirements of their jobs (Purcell et al., 2003). However, this relationship may depend on the hierarchical level. For example, employees with poor skills may become demotivated by complex tasks (Bos-Nehles et al., 2013). Also, managers have more varied and challenging positions that can provide intrinsic motivation (Bayo-Moriones & Bello-Pindado, 2021; Hauff et al., 2021). The most common motivation-enhancing practices are related to extrinsic incentives (e.g., pay-for-performance or profit sharing) or to non-economic forms of motivation, such as performance appraisal, job security, recognition, internal promotion, and work-life balance opportunities. In contrast, intrinsic motivation practices are less common in previous literature (Marín-García & Martinez-Tomas, 2016).

The opportunity dimension (O) concerns employee involvement in decision-making. Previous research suggests that motivated employees who can perform will not foster performance unless organisations provide appropriate opportunities to apply their skills (Jiang et al., 2012). Additionally, empowered employees tend to exhibit higher levels of job satisfaction (Bastida et al., 2022; Fabi et al., 2015). Organisations willing to foster participation should reduce the distance between employees and management, promote dialogue across organisational hierarchies, implement knowledge-sharing procedures, and provide employees with greater autonomy in performing their tasks (Appelbaum et al., 2000; Mackintosh et al., 2025). Some authors argue that the positive effect of this bundle on job satisfaction is more substantial for line managers than for workers, as they perform activities such as planning and controlling (Bayo-Moriones & Bello-Pindado, 2021).

The HRM literature has considered the AMO model from different perspectives, depending on how HR practice bundles interact. However, scholars have not agreed on which of these perspectives better explains the relationship between the three AMO bundles (Knies & Leisink, 2014). We have found several perspectives. The classic ones are the additive (or summative) and the multiplicative (interactive or complementary) approaches. Also, some scholars consider this relationship differently and propose alternative perspectives, such as the combinative approach, the constraining-factor theory, or the singly-necessary-and-jointly-sufficient theory (Dasí et al., 2021; Hauff et al., 2021; Tuuli & van Rhee, 2021). However, the latter's presence in HRM literature is slight.

The additive approach assumes that bundles have independent effects, and increasing levels in one of the three AMO bundles directly and positively contribute to performance (Boxall, 2003; Delery, 1998). Hence, the absence of one factor can be compensated by higher levels in the other two (Dasí et al., 2021; Kim et al., 2015; Morales-Sánchez & Pasamar, 2019). An advantage of the additive approach is that different combinations of HR practices can increase performance (Becker & Huselid, 1998). In support of this approach, some scholars point out that each AMO bundle aims at different objectives, and that some organisations might only need specific ability-, motivation-, or opportunity-enhancing practices to enhance performance (Kroon et al., 2013). However, other authors state that this approach cannot capture the synergies among HR practices (Boon et al., 2019). Also, it seems reasonable to assume that a minimum level in each dimension is required, as, for instance, highly motivated employees will not perform better if they lack the necessary abilities (Marín-García & Martinez-Tomas, 2016). Nonetheless, despite repeated calls to adopt other approaches, most studies use an additive approach (Boon et al., 2019; Hauff et al., 2025; Marín-García & Martinez-Tomas, 2016), and only a few combine practices in other ways (Boon et al., 2019).

The multiplicative approach posits that ability, motivation, and opportunity must be present to some degree for performance to occur (Tuuli & van Rhee, 2021); if any of these is low, performance will be affected (Bos-Nehles et al., 2013; Vroom, 1964). This makes sense since the lack of abilities, for instance, can seldom be counterbalanced by motivation or organisational support (Dasí et al., 2021). In this vein, some authors argue that if any factor is absent, performance is zero (Ozcelik & Uyargil, 2015). We have found only a few articles that consider the multiplicative approach, either theoretically or practically. In this line, ability is essential for performance (Alba et al., 2021). However, both motivation and opportunities are also important (Bos-Nehles et al., 2013). Other authors suggest that ability and motivation affect performance, and opportunity moderates the effect of motivation (Knies & Leisink, 2014). Likewise, some scholars claim that motivation enhances performance and is moderated by opportunities and abilities (Hughes, 2007). However, most studies have examined synergistic effects between two bundles (two-way interactions) (Alba et al., 2021; Beltrán-Martín & Bou-Llusar, 2018; Guerci et al., 2017; Pham et al., 2020). We will follow this predominant trend in our analysis. According to these authors, the multiplicative approach is supposed to consider better the synergies between the categories of the AMO model (Kim et al., 2015; Obeidat et al., 2010; Dasí et al., 2021). Therefore, we expect that multiplicative approaches will perform better than the additive perspective in explaining the relationship between AMO and job satisfaction.

3. Methodology

Our data source is the Survey of Adult Skills, which forms part of the International Assessment of Adult Competencies (PIAAC) program (OECD, 2016). PIAAC is a worldwide study of adults aged 16 to 65, designed to be internationally comparable and focused on analysing skill-formation outcomes. The sampling unit is the individual, and the design employs a stratified, multistage, clustered area sample (Kirsch et al., 2020). The first round (2011–2012) included 24 countries, among them Spain, and results were released between 2013 and 2018.

The Spanish sample comprises 6,055 observations, but we restrict it to employed or self-employed workers, yielding 3,386 cases (53.5% men and 46.5% women). Most participants work in the private sector (77.8%). Regarding company size, 36.9% work in microenterprises, 25.6% in small enterprises, 15.1% in medium-sized enterprises, and 11.2% in large organisations.

Before describing the variables, a clarification of the measurement approach is warranted. Following recent conceptual work on the AMO framework (Bos-Nehles et al., 2023), we adopt an employee-centred approach and operationalise the three dimensions through employees' perceptions of AMO-enhancing working conditions rather than through employers' reported formal HRM practices. This choice is consistent with the argument that HRM practices shape employee attitudes through the ways employees experience them (Purcell et al., 2003).

Job satisfaction is the dependent variable, measured with a single global item rated on a 1 (extremely satisfied) to 5 (extremely dissatisfied) scale, with higher scores indicating greater dissatisfaction. Prior literature supports the validity of global measures (Bonavia & Marin-Garcia, 2019; Hauff et al., 2021; Martinez-Tomas & Cuevas-Lopez, 2026; Tett & Meyer, 1993).

In this study, ability is conceptualised from a dynamic perspective: it refers to employees' ongoing development and maintenance of job-relevant knowledge and skills through workplace learning activities, rather than a static measure of accumulated competencies. In this sense, Ability is proxied through three learning-at-work items (learning from co-workers/supervisors, learning by doing, and staying up to date), rated on a 5-point frequency scale (Hauff et al., 2021; Juarez-Tarraga et al., 2019). This conceptualisation also explains why formal educational attainment was not used as the primary measure of ability: the educational level is a relatively stable prior stock, whereas our interest lies in the process through which job-relevant capabilities are maintained and developed; educational attainment and PIAAC's direct skill assessments will be used to analyse possible heterogeneity and robustness in future research (Dasí et al., 2021). We acknowledge that these indicators constitute a specific operationalisation of the ability dimension, centred on capability development at work, and not an exhaustive measure of it. Learning from others, for instance, partly depends on the opportunity to learn. Learning activities can promote job satisfaction when their focus and usefulness align with employee expectations (Fuentes-del-Burgo & Navarro-Astor, 2013).

Within the AMO framework, motivation expresses employees' willingness to commit to specific behaviours. This study examines a specific facet of that willingness: a self-determined, intrinsic learning orientation (the autonomous disposition to learn, explore, relate new ideas, and delve into problems). No claim is made to represent all forms of motivation. Extrinsic incentives, rewards, and motivation induced by HRM policies fall outside the scope of this measure.

Motivation is measured using six items related to self-determined learning orientation, also on a 5-point scale (Edgar et al., 2020). People who relate new ideas to real life, such as those who enjoy learning new things, delve into problems, or figure out how different ideas fit together, are usually concerned with improving their knowledge. Additionally, employees with a higher level of self-determination tend to feel more satisfied with their jobs and exhibit a greater willingness to engage in assigned tasks and to generate and develop new ideas (Sarmah et al., 2022). Respondents answered six questions that were previously used as indicators of intrinsic motivation or goal orientation (Ryan & Deci, 2020). Previous literature shows that these variables predict both learning and skills achievement (Gorges et al., 2017).

We included five PIAAC questionnaire items on participatory decision-making and job autonomy to measure employees' opportunities for participation. Respondents were required to indicate how often they planned their activities and organised their time, and to what extent their current job allowed them to decide the sequence of tasks, how to perform the work, and the pace of work. Items were measured using a 5-point scale.

The management position was used as an observed heterogeneity variable and measured with a dichotomous question (yes/no) asking whether people supervise the work of other employees. Consistent with previous studies (Dasí et al., 2021), we also include the frequency with which they encounter complex problems (ill-defined, requiring goal definition, resolving impasses, and navigating multiple technology environments) as an observed heterogeneity variable. This item was measured using a 5-point scale.

In line with previous research, we include the following control variables: age, economic sector (private, public, or non-profit), and company size (Felstead et al., 2015; Juarez-Tarraga et al., 2019; Schouteten et al., 2021).

Since we use secondary data, we employ partial least squares regression (PLS) to assess the predictive validity of the models. Additionally, we will utilise latent variable scores in subsequent analyses outside the structural model context to identify potential heterogeneity variables and assess the models' out-of-sample predictive capacity (de-Juana-Espinosa & Rakowska, 2018; Marin-Garcia & Alfalla-Luque, 2019; Sarstedt et al., 2022). The analyses have been carried out using SmartPLS version 4.1.1.4 (Ringle & Wende, 2024) and IBM SPSS Statistics for Windows, Version 22.0 (IBM Corp., 2022)

4. Results

Table S1 (in supplementary material) summarises the descriptive statistics. All item loadings exceed 0.7 except I_Q04b (0.668) (Table S2 in the supplementary). Cronbach's α and ϱA values range from 0.70 to 0.95, except for ability, which is near the cut-off value (0.675). Average variance extracted (AVE) values are above 0.50, and discriminant validity (Table S3 in the supplementary) is confirmed through Heterotrait-Monotrait Ratio of Correlations (HTMT) and the Fornell-Larcker criterion (Marin-Garcia & Alfalla-Luque, 2019; Sarstedt et al., 2022). VIF values are below 2.2.

Figures 1 and 2 compare the additive and multiplicative models. Both show low explanatory power ($R2=0.064$ and 0.073, respectively) and similar blindfolding-based cross-validated redundancy measures ($Q2=0.059$ for the additive model; $Q2=0.066$ for the multiplicative model). Control variables show a significant effect, similar to the direct effect of motivation, but are less pronounced than the effects of ability and opportunity. All direct path coefficients are significant since zero is not included in the bootstrap confidence interval, and p-values < 0.05. However, concerning the path coefficient relevance, all f2 values are below 0.02 and therefore have little relevance. Only the ability reaches the lowest value (Table 1).

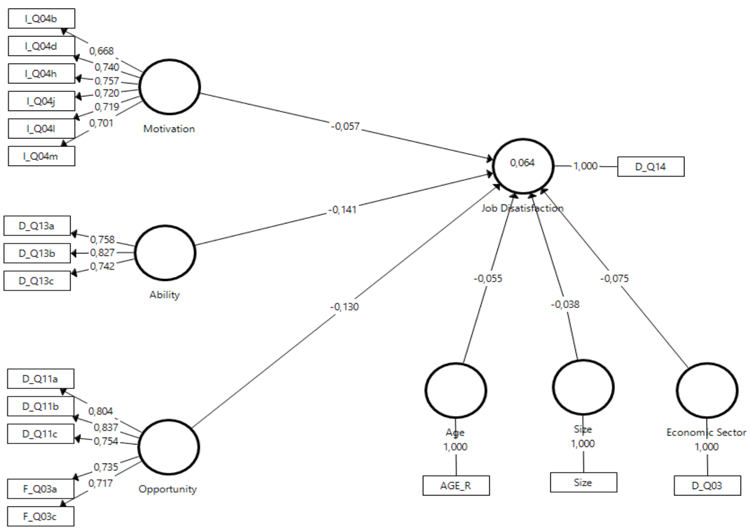

Figure 1. Additive relationships model

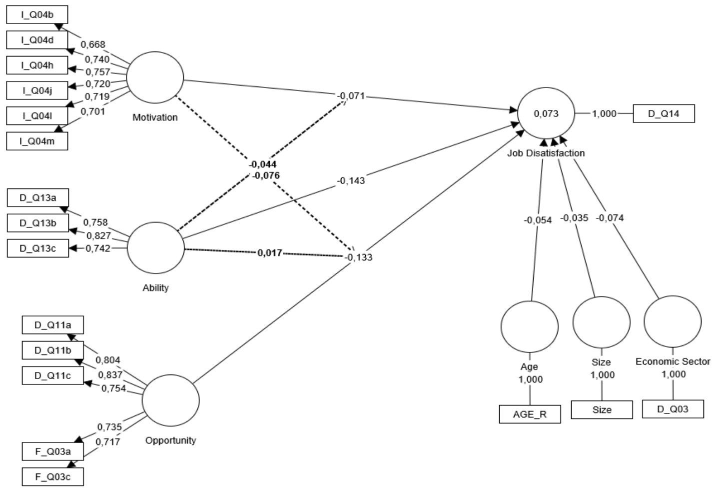

Figure 2. Multiplicative model

Direct model	Path	f2	Standard Deviation	T Statistics	P Values	2.5%	97.5%
Age → Job Dissatisfaction	-0,055	0,003	0,018	3,058	**0,002**	-0,090	-0,020
Economic Sector → Job Dissatisfaction	-0,075	0,005	0,016	4,636	**0,000**	-0,106	-0,043
Size → Job Dissatisfaction	-0,038	0,001	0,018	2,147	**0,032**	-0,072	-0,003
Ability → Job Dissatisfaction	-0,141	0,020	0,018	7,678	**0,000**	-0,179	-0,107
Motivation → Job Dissatisfaction	-0,057	0,004	0,019	2,997	**0,003**	-0,098	-0,023
Opportunity → Job Dissatisfaction	-0,130	0,017	0,019	6,814	**0,000**	-0,167	-0,092
Multiplicative model	**Path**	**f2**	**Standard Deviation**	**T Statistics**	**P Values**	**2.5%**	**97.5%**
Age → Job Dissatisfaction	-0,054	0,003	0,018	3,044	**0,002**	-0,088	-0,018
Economic Sector → Job Dissatisfaction	-0,074	0,005	0,016	4,545	**0,000**	-0,106	-0,042
Size → Job Dissatisfaction	-0,035	0,001	0,018	1,987	**0,047**	-0,069	0,001
Ability → Job Dissatisfaction	-0,143	0,020	0,018	7,847	**0,000**	-0,179	-0,108
Motivation → Job Dissatisfaction	-0,071	0,005	0,019	3,817	**0,000**	-0,111	-0,039
Opportunity → Job Dissatisfaction	-0,133	0,017	0,019	6,966	**0,000**	-0,171	-0,097
AO → Job Dissatisfaction	0,017	0,000	0,019	0,856	**0,392**	-0,021	0,054
MA → Job Dissatisfaction	-0,044	0,002	0,019	2,342	**0,019**	-0,080	-0,007
MO → Job Dissatisfaction	-0,076	0,007	0,020	3,824	**0,000**	-0,115	-0,037

Table 1. Path coefficients for additive & multiplicative models

Two-way interactions become significant when ability moderates the motivation–dissatisfaction relationship and when motivation moderates the opportunity–dissatisfaction link (Figures 3 and 4). In both cases, higher ability or opportunity amplifies the negative effect of motivation on dissatisfaction. When ability is low (below one standard deviation of the mean), it hardly alters the direct effect of motivation, and the slope remains almost flat. However, when ability is high (above one standard deviation), the slope becomes steeper, indicating that employees with high ability experience lower dissatisfaction than those with low motivation. The green line lies consistently below the red line, and the gap between them widens, meaning that the interaction effect is stronger than the mere addition of direct effects.

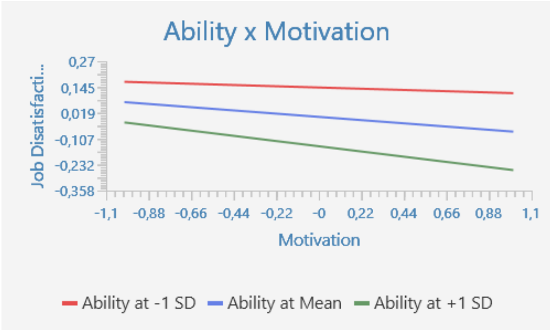

Figure 3. Slope analysis (Ability-Motivation)

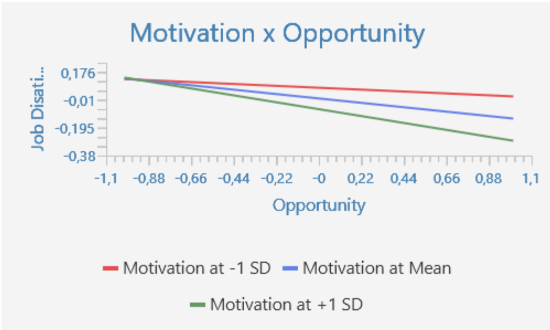

Figure 4. Slope analysis (Motivation-Opportunity)

A similar pattern appears in the interaction between motivation and opportunity. Among employees with low opportunity, dissatisfaction levels remain similar regardless of motivation. As opportunities increase, job dissatisfaction decreases more sharply among highly motivated employees (green line) than among those with low motivation (red line). At low opportunity, both lines intersect, but as opportunity rises, they diverge, with the green line remaining lower. In this case, the difference in slopes is also statistically significant, reinforcing the claim that motivation becomes more relevant when paired with favourable contextual conditions.

According to the BIC value (Table S4 in the supplementary material), the multiplicative model has better predictive capacity, with a smaller BIC (-158.89 vs -152.56 for the additive model). Out-of-sample predictive power is valid for both the additive and the multiplicative models, as they outperform linear regression (Table 2). Although the additive model exhibits lower Mean Absolute Error (MAE) values, the cross-validation predictive ability test (CVPAT) analysis demonstrated that the differences in out-of-sample predictive capacity are not statistically significant. Considering these findings, we conclude that the multiplicative model, which demonstrates superior in-sample predictive power (higher R^2 and better BIC values), is the best specification for this study's research objectives.

	PLS			LM			Dif PLS-LM	
	RMSE	MAE	Q^2_predict	RMSE	MAE	Q^2_predict	RMSE	MAE
Direct model	0,768	0,525	0,059	0,769	0,530	0,056	-0,001	-0,004
Multiplicative model	0,765	0,528	0,066	0,767	0,531	0,062	-0,001	-0,003

Table 2. PLS predicts Job dissatisfaction (D_Q14)

We have previously analysed the measurement models' invariance to assess whether differences arise when comparing employees with or without managerial positions, or when comparing people facing complex problems. We find partial measurement invariance in the multiplicative model when comparing people in managerial positions. However, it does not apply within the opportunity construct when comparing people facing complex problems to those facing simple problems (D_Q11c weights vary significantly across subsamples). Similarly, we find partial measurement invariance in the additive model when comparing employees in managerial positions; however, this does not hold for individuals facing complex problems. Again, differences are found within the opportunity construct (D_Q11c). Employees in managerial positions commonly exhibit high values across the three bundles: ability, motivation, and opportunity. Also, they are frequently slightly older, less dissatisfied, and more likely to work for larger companies. The same characteristics apply to people facing complex problems.

As a result of the measurement invariance analysis, we can only compare the paths and R2 values of the employee's subsample with those of the managerial positions subsample. We find significant differences in the ability-job dissatisfaction path in the additive model. Differences among the other paths and R2 values are not significant (see Table S5 in the supplementary material). Concerning the multiplicative model, we find significant differences in the ability-job dissatisfaction path and the ability moderation effect over motivation. Differences among the other paths and R2 values are not significant (see Table S6 in the supplementary material). The ability-job dissatisfaction relationship is more pronounced among individuals who occupy managerial positions (path coefficient: -0.212) than among those without managerial positions (path coefficient: -0.114). Additionally, the interaction between ability and motivation is higher among managers (-0.105) than among non-managers (-0.022).

Although results show significant relationships between the AMO model variables and job dissatisfaction, the strength of these relationships is very low. Observed heterogeneity cannot help to find stronger relationships between the groups. Therefore, we complete the analysis by verifying unobserved heterogeneity (Table 3). The 5-segment solution performs the best for AIC, BIC, CAIC, HQ, and MDL5. The 3-segment solution achieves intermediate performance in almost all indicators, with the best results for NFI. Moreover, the 5-segment solution allows groups of a sufficient size (more than 10% of the sample). Finally, R2 values within the 5-segment solution are higher than in the original samples (all segments above 0.42). Therefore, we propose considering the five segments.

FIMIX selection criteria	1 segments	2 segments	3 segments	4 segments	5 segments	6 segments
AIC (Akaike's Information Criterion)	8732.00	5713,147099	4291,729325	4252,911373	**3529,366922**	3590,127249
AIC3 (Modified AIC with Factor 3)	8739.00	5728,147099	4314,729325	4283,911373	**3568,366922**	3637,127249
AIC4 (Modified AIC with Factor 4)	8746.00	5743,147099	4337,729325	4314,911373	**3607,366922**	3684,127249
BIC (Bayesian Information Criteria)	8774.36	5803,931546	4430,932145	4440,532564	**3765,406485**	3874,585184
CAIC (Consistent AIC)	8781.36	5818,931546	4453,932145	4471,532564	**3804,406485**	3921,585184
HQ (Hannan Quinn Criterion)	8747.20	5745,725819	4341,683362	4320,240727	**3614,071593**	3692,207238
MDL5 (Minimum Description Length with Factor 5)	8999.83	6287,069336	5171,743423	5439,01733	**5021,564739**	5388,416926
LnL (LogLikelihood)	-4359.00	**-2841,573549**	-2122,864663	-2095,455686	-1725,683461	-1748,063624
EN (Entropy Statistic - Normed)	0.00	0,700093705	0,764767987	0,718800504	0,774258265	**0,788248109**
NFI (Non-Fuzzy Index)	0.00	0,76673324	**0,783609627**	0,706572109	0,747750606	0,748262412
NEC (Normalised Entropy Criterion)	0.00	**942,005673**	738,8637539	883,2476157	709,0547898	665,1126912
POS Segment sizes (% of the sample)						
Seg1	1	54,63	33,65	18,62	16,68	21,04
Seg2		45,37	28,62	26,93	23,11	13,44
Seg3			37,73	21,04	10,41	23,69
Seg4				33,40	16,71	6,02
Seg5					33,08	4,81
Seg6						31,01
POS-R2						

FIMIX selection criteria	1 segments	2 segments	3 segments	4 segments	5 segments	6 segments
Seg1	0,06	0,32	0,27	0,56	0,56	0,48
Seg2		0,54	0,45	0,35	0,42	0,60
Seg3			0,53	0,70	0,76	0,45
Seg4				0,44	0,63	0,81
Seg5					0,43	0,90
Seg6						0,39

Table 3. Unobserved heterogeneity analysis (selection criteria from FIMIX, and segment sizes and R2 from POS)

5. Discussion

HRM systems are based on the premise that the combined effect of HRM practices is greater than the sum of their individual effects (Fabi et al., 2015), due to complementarities among practices (Delery, 1998). According to the AMO model, integrating skills, motivation, and opportunity bundles is mutually reinforcing (Appelbaum et al., 2000; Boxall & Purcell, 2003). Some authors argue that organisations must adopt all three bundles to guarantee performance (MacDuffie, 1995). However, most studies employ an additive approach that may not capture synergies (Boon et al., 2019). This study responds to calls for testing interactions by comparing additive and multiplicative models.

Contrary to expectations, the full-sample results reveal limited predictive capacity: none of the models explains more than 10% of the variance in job satisfaction, which falls below the thresholds we adopted for assessing a standalone explanatory model. Three considerations help to interpret this result. First, the purpose of this study is comparative rather than explanatory in absolute terms. Both specifications were estimated on the same data, constructs, and controls; consequently, the multiplicative model's superior performance (higher R2, lower BIC, significant interaction terms) indicates how AMO bundles combine, regardless of the overall variance explained.

Second, several measurement and design features attenuate the observable effects. Job satisfaction is captured through a single global item, whose limited reliability deflates observed correlations (Tett & Meyer, 1993), and AMO perceptions are relatively distal antecedents of a global attitude. Moreover, the models could not include well-established predictors that are unavailable in PIAAC. At the individual level, personality traits and tenure vary across employees and play important roles in determining job satisfaction levels (Al-Doghan et al., 2019). Job-level factors such as teamwork dynamics or working conditions related to physical comfort (Grawitch et al., 2009; Herzberg, 1974), and organisational-level variables such as leadership behaviour, fair company policies, extrinsic rewards, and promotion opportunities (Herzberg, 1974; Prentice, 2022), were also absent from our analytical framework. Individual-level studies based on large-scale secondary surveys typically report similarly modest effect sizes for workplace learning and participation variables (Felstead et al., 2015).

Third, the unobserved heterogeneity analysis indicates that the modest pooled R^2 largely reflects the aggregation of heterogeneous employee profiles rather than a weakness of the AMO framework itself. When five latent segments are distinguished, R^2 values rise to 0.42-0.76, and several paths reverse their sign across segments. As a matter of fact, intrinsic motivation reduces dissatisfaction in Segments 1, 3, and 4, but increases it in Segment 5. Averaging such opposing responses in the pooled sample cancels out effects and deflates the variance explained. The low full-sample explanatory power should therefore be read as evidence that the AMO–job satisfaction relationship is profile-contingent. This carries implications for both theory and practice: pooled estimates may systematically understate the explanatory value of the AMO framework, so researchers should routinely test for unobserved heterogeneity before drawing conclusions from full-sample results; and HR managers should be cautious about one-size-fits-all bundles, as diagnosing employee profiles may be a precondition for configuring effective AMO-enhancing practices.

Results show the most substantial effect for ability, followed by opportunity, while intrinsic motivation has a weaker influence, consistent with previous research (Beltrán-Martín & Bou-Llusar, 2018; Guerci et al., 2017; Pham et al., 2020; Vermeeren, 2017). Other studies argue that ability is the stronger predictor (Jyoti & Rani, 2017) or suggest that skills affect outcomes, with opportunities or motivation moderating this effect (Bos-Nehles et al., 2013; Guerci et al., 2017).

The comparatively weak contribution of motivation must be interpreted in the light of its operationalisation. Our measures capture intrinsic learning orientation, whereas most prior AMO research examines extrinsic motivation-enhancing practices, such as pay-for-performance or profit sharing (Marín-García & Martinez-Tomas, 2016), which typically show weak links with job satisfaction. Our results, therefore, do not imply that motivation-enhancing practices are irrelevant; rather, they indicate that intrinsic motivation, considered in isolation, adds little direct explanatory power once ability- and opportunity-related perceptions are taken into account. Interestingly, its influence emerges mainly through interactions: intrinsic motivation reduces dissatisfaction, particularly when combined with high ability or ample opportunities. This pattern is consistent with self-determination theory, which holds that autonomous motivation unfolds its benefits under supportive conditions (Ryan & Deci, 2020), and it reinforces the added value of the multiplicative specification.

The multiplicative model performs slightly better than the additive model, in line with previous findings (Dasí et al., 2021). Significant effects are observed in ability–motivation and motivation–opportunity interactions, but not in ability–opportunity interactions. In line with our study, some authors argue that considering double rather than triple interactions is more convenient (Bos-Nehles et al., 2013).

Observed heterogeneity reveals that the AMO model predicts job satisfaction more accurately among managerial employees (R^2 = 0.11) than among non-managers (R^2 = 0.07), and that both the ability-job dissatisfaction path and the ability × motivation interaction are significantly stronger among managers. Three mechanisms may explain this pattern. First, managerial jobs provide greater discretion to apply what is learned, so ability-enhancing exposure translates more directly into effective performance and, consequently, into job satisfaction (Bayo-Moriones & Bello-Pindado, 2021). Second, managerial roles demand a broader range of skills, thereby increasing both the salience and the perceived usefulness of learning opportunities (Beltrán-Martín & Bou-Llusar, 2018; Subramony, 2009). Third, line managers are frequently implementers of HRM practices, which intensifies their exposure to AMO-enhancing conditions (Bos-Nehles et al., 2013). The stronger ability × motivation interaction among managers is consistent with this interpretation: when the job allows newly acquired competencies to be deployed, intrinsic motivation operates as a multiplier of the benefits of learning rather than merely as an additive ingredient.

The unobserved heterogeneity analysis reveals substantial differences in the AMO model's predictive performance across sample segments. While the original model yields R^2 values of 6%–11% (depending on the model and managerial status), identifying five segments significantly improves the fit, with R^2 values ranging from 0.42 to 0.76. This suggests that the AMO–job satisfaction relationship is not uniform but varies across employee profiles (Table S7 in the supplementary material).

The five segments reveal three broad patterns in how ability, motivation, and opportunity combine to shape job satisfaction (Figure 5). In the first pattern, the AMO logic operates as theorised: the three dimensions jointly reduce dissatisfaction, achieving the highest model fit (Segment 3, R^2 = 0.76), with decision-making opportunities playing a prominent role in a variant of this pattern (Segment 4, R^2 = 0.56). In the second pattern, satisfaction is driven mainly by one dominant dimension: intrinsic motivation in Segment 1 (R^2 = 0.42) or workplace learning in Segment 2 (R^2 = 0.58), while the other dimensions show minimal or counterintuitive effects. In the third pattern, intrinsic motivation emerges as the strongest source of dissatisfaction (Segment 5, R^2 = 0.54), suggesting that high motivation creates expectations that the work environment fails to meet. The figure visually summarises the pattern of effects for each segment.

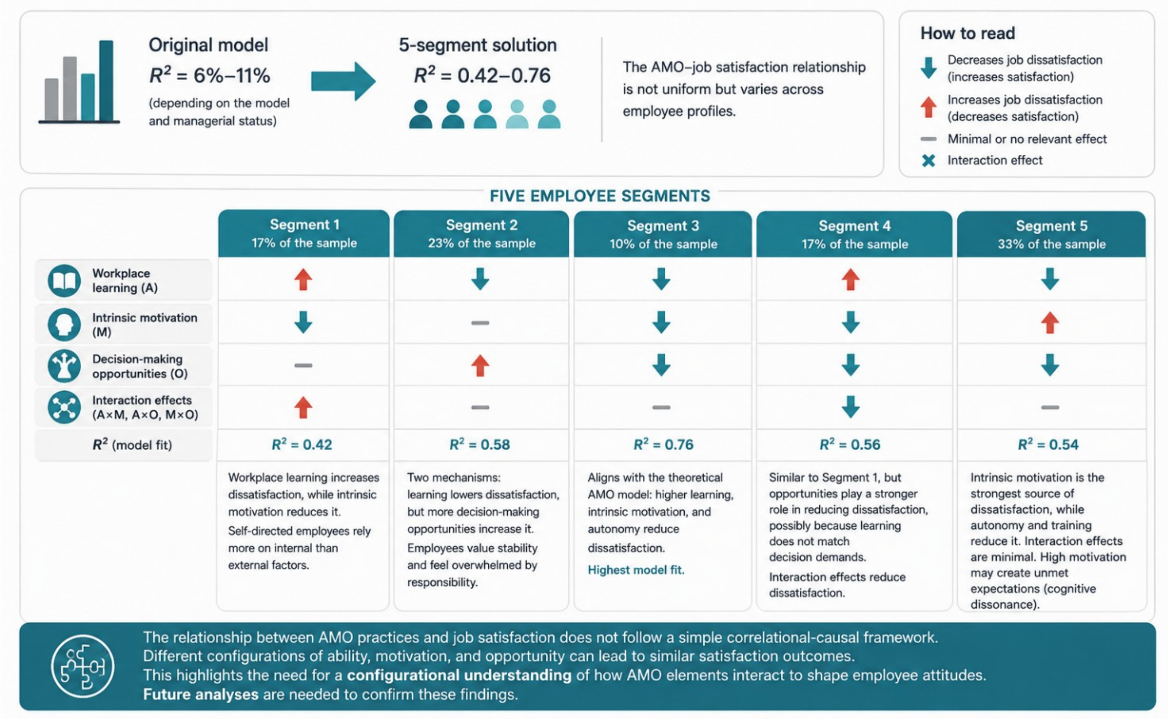

Figure 5. Unobserved Heterogeneity in the AMO-JS Relationship

Segment 1 (17% of the sample) indicates that workplace learning increases dissatisfaction, while intrinsic motivation significantly reduces it, suggesting that self-directed employees rely more on internal than external factors. Segment 4 (17%) shares this pattern, but decision-making opportunities play a stronger role in reducing dissatisfaction, possibly because the learning received does not match decision demands. In this segment, interaction effects reduce dissatisfaction, whereas in Segment 1, they increase it.

Segment 2 (23%) is driven by two opposing mechanisms: workplace learning lowers dissatisfaction, but greater decision-making opportunities increase it, suggesting that these employees value stability and may feel overwhelmed by additional responsibility. Segment 3 (10%) aligns with the theoretical AMO model, in which higher learning, intrinsic motivation, and autonomy contribute to reduced dissatisfaction, resulting in the highest model fit (R^2 = 0.76). Segment 5 (33%) shows intrinsic motivation as the strongest source of dissatisfaction, while autonomy and workplace training reduce it; interaction effects are minimal. For these employees, high motivation may lead to expectations that the work environment fails to meet, consistent with Festinger's cognitive dissonance theory.

These patterns suggest that the relationship between AMO practices and job satisfaction may not follow a simple correlational-causal framework. Instead, different configurations of the predictor variables may yield equivalent satisfaction outcomes, suggesting a more complex, configurational understanding of how ability, motivation, and opportunity interact to influence employee attitudes. However, further analyses are needed to confirm these findings.

6. Conclusion

Our study makes a significant contribution to the HRM literature in three ways. First, we assess the differences between additive and multiplicative approaches of the AMO model. There is no consensus on how AMO bundles interact, and few studies have analysed this. We explore the model's predictive capacity at the individual level, focusing on job satisfaction, which some authors argue may mediate the relationship between HR systems and organisational performance. Therefore, analysing how HRM policies affect employee well-being and satisfaction is valuable.

The PIAAC survey provides a large and representative sample; however, we cannot intervene in its design to include other factors related to high-involvement practices or variables that moderate job satisfaction. We also lack longitudinal data, which limits causal inference —a problem already noted in the HRM literature, as longitudinal studies are both costly and time-consuming.

A second limitation concerns the operationalisation of the constructs, which is constrained by the data's secondary nature. The objective stock of competencies that employees possess is not directly measured; ability, from a dynamic perspective, is captured by the development and maintenance of job-relevant capabilities through workplace learning activities. Likewise, not all forms of motivation are covered: our measure captures a self-determined, intrinsic learning orientation rather than extrinsic incentives, task-specific motivation, or motivation induced by HRM practices. This employee-perception approach is consistent with the argument that HRM practices influence attitudes through the way employees experience them (Bos-Nehles et al., 2023; Purcell et al., 2003), and the items employed have been used for these purposes in previous PIAAC-based research (Felstead et al., 2015; Gorges et al., 2017; Hauff et al., 2021). Nevertheless, alternative operationalisations could alter the relative weight of the three dimensions and even the outcome of the comparison between the additive and multiplicative specifications, so our findings should be generalised with caution.

A third consideration concerns the currency of the data, collected in Spain in 2011–2012. Since our research question addresses the specification of the AMO model rather than the estimation of current satisfaction levels, the age of the data does not compromise the internal logic of the comparison. Nevertheless, post-pandemic transformations in work arrangements, such as the spread of remote work and heightened expectations of autonomy and flexibility, may have altered the relative weight of the AMO dimensions in shaping job satisfaction.

Our research suggests several future lines. First, applying the same analysis in other countries would help determine whether sociocultural differences affect the model. In addition, the Second Cycle of PIAAC (collected in 2022–2023, with first results released in December 2024) includes socio-emotional and work-environment variables, providing a direct opportunity to replicate this study using current data and to enrich the models with new predictors. Another approach would be to utilise different data sources to verify the consistency of the results. We also controlled for company size, sector, and age; future studies could examine other organisational, job-level, or individual factors, such as job design, culture, policies, leadership, or personality traits.

In addition, we compared additive and multiplicative models, but few studies have evaluated other proposals, such as the constraining-factor or the Singly-Necessary-and-Jointly-Sufficient theory (Dasí et al., 2021; Siemsen et al., 2008; Tuuli & van Rhee, 2021). The constraining-factor view holds that the lowest AMO dimension constrains the others, such that increasing the weakest one strengthens the overall effect (Siemsen et al., 2008; Tuuli & van Rhee, 2021). HRM policies aimed at enhancing motivation and opportunities will be severely affected if employees lack the necessary abilities to perform, thereby constraining the ability dimension. This assumption is based on empirical evidence that typically indicates additive effects of HRM bundles (Tuuli & van Rhee, 2021). Some evidence supports this over additive or multiplicative approaches in predicting some employee behaviours (Siemsen et al., 2008). Other investigations, however, have yielded mixed results (Dasí et al., 2021). In contrast, the Singly-Necessary-and-Jointly-Sufficient theory assumes each AMO factor is necessary and that the lowest one acts as a bottleneck, which cannot be compensated for by higher levels in the other two. This logic differs from additive sufficiency and requires methods such as Necessary Condition Analysis (NCA) rather than regression (Hauff et al., 2021; Tuuli & van Rhee, 2021).

Most empirical studies follow an additive sufficiency logic, assuming that the absence of HRM practices in one AMO domain can be compensated for by HRM practices in the others (Hauff et al., 2021). However, this does not align with the notion of necessity implied in the original AMO model, which requires single HRM activities that cannot be compensated for to ensure performance. The necessary condition cannot be analysed using regression-based methodologies, suggesting the need for necessary condition analysis (NCA).

Future research should also adopt configurational approaches to AMO and job satisfaction, moving beyond linear models. Qualitative Comparative Analysis (QCA) or fuzzy-set methods could reveal how different AMO combinations produce equivalent satisfaction outcomes, recognising multiple pathways to high job satisfaction across organisations.

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Authors' contributions

Both authors contributed equally to all sections of the article: conceptualisation, methodology, formal analysis, investigation, writing, review and editing.

Data availability

Data available in a public repository. This research is based on a public dataset available at: https://www.oecd.org/en/data/datasets/piaac-1st-cycle-database.html (OECD, Programme for the International Assessment of Adult Competencies, PIAAC, 1st Cycle Database).

Use of Artificial Intelligence

Artificial intelligence tools were used exclusively for translation-related language corrections. No AI tools were used to generate or analyse data, text, or graphics.

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Appendix A

Supplementary material for Comparing predictive validity of additive versus multiplicative AMO models to explain attitudinal outcomes, job satisfaction

Data analysis procedures

We use a four-step process for evaluating the measurement model validity:

1. Item reliability: Loadings > 0.7
2. Internal consistency reliability: Cronbach's α values and Dijkstra and Henseler ϱA values are to be between 0.70 and 0.95
3. Convergent validity test: average variance extracted (AVE) values > 0.50
4. Discriminant validity test: Heterotrait-monotrait ratio of correlations (HTMT) < 0.90, and Fornell-Larcker criterion threshold (although the latter is not very precise if the loadings of all the indicators are in a very narrow range of values (0.67-0.84), as it happens with our data) (Marin-Garcia & Alfalla-Luque, 2019a; Sarstedt et al., 2022).

We use a five-step process for evaluating the model structure (Marin-Garcia & Alfalla-Luque, 2019a):

1. VIF values < 3
2. In-sample explanatory power:
   - R2 values: Poor (0.1-0.25); moderate (0.25-0.45); high (0.5-0.75). R2 values above 0.8 may indicate overfitting.
   - Blindfolding-based cross-validated redundancy measure: Q2 values (poor predictive relevance: 0-0.25; moderate: 0.25-0.50; high: >0.50)
3. Out-of-sample predictive power:
   - Using K-folds = 10 & 10 repetitions: RMSE or MAE values must be smaller in PLS than when using the LM benchmark
4. Path coefficient significance: p-values of t-distribution < 0.05; or bootstrap confidence interval does not include 0
5. Path coefficient relevance:
   - f2 values: low >0.02; moderate >0.15, high >0.35. Path values near 0 have little relevance

When comparing competitive models, such as additive versus multiplicative effects, the model with the lower BIC value is considered the best in terms of in-sample predictive performance (Danks et al., 2020; Sarstedt & Danks, 2022). We also verify that the model with fewer PLS predictors that predicts errors will be the most suitable for out-of-sample predictive performance (Marin-Garcia & Alfalla-Luque, 2019b; Shmueli et al., 2016). The results of PLS Predict will be checked with CVPAT to determine whether the prediction differences between the additive and multiplicative models are significant (Sharma et al., 2023).

To control observed heterogeneity, we analyse the invariance of the measurement model, focusing on manager position and complex problem items. The procedure to assess measurement invariance of the composite model (MICOM) consists of 5000 permutations and a significance level equal to 5% with two tails. To control the measurement model, we analyse whether compositional invariance is fulfilled (permutation p-values > 0.05 indicate that construct indicator weights do not differ significantly between groups). Next, we focus on mean differences and logarithms of variance values. If permutation-based confidence intervals include the mean and logarithm of the' original variance values, then we consider full measurement invariance. On the contrary, we conclude that there is partial measurement invariance, which is a sufficient condition for comparing group paths and detecting significant path differences (Marin-Garcia & Alfalla-Luque, 2019a).

We complete the analyses by checking unobserved heterogeneity. We use finite mixture partial least squares (FIMIX-PLS), a latent class segmentation method, to uncover unobserved heterogeneity in the multiplicative structural model. We choose the number of segments for which AIC, BIC, CAIC, HQ, MDL5, and LNL have lower values; or those for which EN, NFI, and NEC have higher values; and show enough subjects included in the segment. AIC tends to bias segment recommendation upwards, whereas MDL5 tends to bias it downwards. If there are more than one segment with a high number of cases, data will be classified using prediction-oriented segmentation (POS) (Marin-Garcia & Alfalla-Luque, 2019b).

Additional tables and figures

Category	Item	N	Min.	Max.	Mean	Std. Deviation	Skewness	Stat Kurtosis
Job Satisfaction	D_Q14 Current work - Job satisfaction	3374	1	5	2.12	.797	1.082	1.878
Control Variable	AGE_R Person resolved age from BQ and QC check (derived)	3386	16	65	40.61	11.137	.029	-.821
Control Variable	D_Q03 Current work - Economic sector	3365	1	3	1.23	.449	1.686	1.804
Control Variable	Size- Amount of people working for an employer	3010	1	4	2.01	1.044	.652	-.825
Ability	D_Q13a Current work - Learning - Learning from co-workers/supervisors	3023	1	5	3.36	1.527	-.298	-1.423
Ability	D_Q13b Current work - Learning - Learning-by-doing	3372	1	5	3.87	1.421	-.874	-.730
Ability	D_Q13c Current work - Learning - Keeping up to date	3374	1	5	3.43	1.549	-.329	-1.479
Motivation	I_Q04b About yourself - Learning strategies - Relate new ideas to real life	3369	1	5	3.43	.955	-.315	-.076
Motivation	I_Q04d About yourself - Learning strategies - Like learning new things	3385	1	5	4.22	.778	-1.008	1.507
Motivation	I_Q04h About yourself - Learning strategies - Attribute something new	3382	1	5	3.81	.893	-.595	.400
Motivation	I_Q04j About yourself - Learning strategies - Get to the bottom of difficult things	3383	1	5	3.83	.954	-.656	.176
Motivation	I_Q04l About yourself - Learning strategies - Figure out how different ideas fit together	3352	1	5	3.46	1.030	-.383	-.280

Category	Item	N	Min.	Max.	Mean	Std. Deviation	Skewness	Stat Kurtosis
Motivation	I_Q04m About yourself - Learning strategies - Looking for additional info	3385	1	5	4.19	.811	-1.029	1.427
Opportunity	F_Q03a Skill use work - How often - Planning own activities	3373	1	5	3.98	1.556	-1.151	-.407
Opportunity	F_Q03c Skill use work - How often - Organising own time	3372	1	5	4.22	1.430	-1.565	.744
Opportunity	D_Q11a Current work - Work flexibility - Sequence of tasks	3377	1	5	3.23	1.349	-.244	-1.086
Opportunity	D_Q11b Current work - Work flexibility - How to do the work	3376	1	5	3.35	1.291	-.400	-.872
Opportunity	D_Q11c Current work - Work flexibility - Speed of work	3376	1	5	3.30	1.249	-.310	-.810
Observed Heterogeneity	Manager Managing other employees	3375	0	1	.28	.449	.984	-1.033
Observed Heterogeneity	F_Q05b Skill use work - Problem-solving - Complex problems	3369	1	5	2.73	1.417	.210	-1.312

Table S1. Descriptive Statistics

	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	2.5%	97.5%
AGE_R ← Age	1.000	0.000				
D_Q03 ← Economic Sector	1.000	0.000				
D_Q11a ← Opportunity	0.804	0.017	47.930	0.000	0.768	0.834
D_Q11b ← Opportunity	0.837	0.015	54.732	0.000	0.805	0.865
D_Q11c ← Opportunity	0.754	0.021	36.031	0.000	0.709	0.792
D_Q13a ← Ability	0.758	0.029	26.144	0.000	0.698	0.810
D_Q13b ← Ability	0.827	0.019	43.544	0.000	0.786	0.860
D_Q13c ← Ability	0.742	0.028	26.887	0.000	0.683	0.792
D_Q14 ← Job Dissatisfaction	1.000	0.000				
F_Q03a ← Opportunity	0.735	0.026	28.510	0.000	0.681	0.782
F_Q03c ← Opportunity	0.717	0.027	26.864	0.000	0.659	0.764
I_Q04b ← Motivation	0.668	0.035	19.105	0.000	0.593	0.732
I_Q04d ← Motivation	0.740	0.024	30.365	0.000	0.686	0.781
I_Q04h ← Motivation	0.757	0.025	29.853	0.000	0.702	0.801
I_Q04j ← Motivation	0.720	0.029	24.441	0.000	0.653	0.770
I_Q04l ← Motivation	0.719	0.028	25.902	0.000	0.660	0.770
I_Q04m ← Motivation	0.701	0.029	23.853	0.000	0.639	0.754
Size ← Size	1.000	0.000				

Table S2. Outer loadings

	Ability-On-the-job learning	Job Dissatisfaction	Motivation-Learning approach	Opportunity
Ability-On-the-job learning	0.78	0.21	0.30	0.22
Job Dissatisfaction	-0.17	1.00	0.12	0.16
Motivation-Learning approach	0.22	-0.11	0.72	0.19
Opportunity	0.11	-0.15	0.16	0.77

Table S3. Discriminant validity test. Heterotrait-Monotrait ratio (HTMT) in the upper submatrix. Fornell-Larcker criterion on diagonal and lower submatrix

	Additive Model	Multiplicative Model
Fit summary SRMR	0.069	0.069
BIC (Bayesian Information Criteria)	-152.562	-158.891

Table S4. Fit summary and BIC Predictive capacity

Path Coefficients	Original Difference (Manager (0.0) - Manager (1.0))	2.5%	97.5%	Permutation p-Values
Ability → Job Dissatisfaction	0.099	-0.079	0.080	0.015
Age → Job Dissatisfaction	-0.003	-0.083	0.077	0.957
Economic Sector → Job Dissatisfaction	-0.044	-0.073	0.067	0.201
Motivation → Job Dissatisfaction	-0.005	-0.073	0.091	0.908
Opportunity → Job Dissatisfaction	0.031	-0.090	0.077	0.435
Size → Job Dissatisfaction	-0.059	-0.080	0.075	0.137
R Square				
Job Dissatisfaction	-0.031	-0.044	0.028	0.104

Table S5. Path coefficients (additive model)

Path Coefficients	Original Difference (Manager (0.0) - Manager (1.0))	2.5%	97.5%	Permutation p-Values
AM → Job Dissatisfaction	0.083	-0.084	0.080	0.048
AO → Job Dissatisfaction	-0.009	-0.082	0.085	0.837
Ability → Job Dissatisfaction	0.098	-0.079	0.083	0.017
Age → Job Dissatisfaction	-0.012	-0.080	0.078	0.761
Economic Sector → Job Dissatisfaction	-0.040	-0.072	0.070	0.255
MO → Job Dissatisfaction	-0.022	-0.084	0.086	0.621
Motivation → Job Dissatisfaction	0.003	-0.071	0.085	0.945
Opportunity → Job Dissatisfaction	0.039	-0.079	0.084	0.348
Size → Job Dissatisfaction	-0.063	-0.078	0.076	0.108
R Square				
Job Dissatisfaction	-0.040	-0.050	0.030	0.069

Table S6. path coefficients (multiplicative model)

	Segment1	Segment2	Segment3	Segment4	Segment5
Ability-On-the-job learning → Job dissatisfaction	0.100	-0.391	-0.293	0.296	-0.286
Motivation-Learning approach → Job Dissatisfaction	-0.637	-0.106	-0.737	-0.483	0.401
Opportunity → Job Dissatisfaction	-0.252	0.441	-0.194	-0.569	-0.424
Ability-On-the-job learning x Motivation-Learning approach → Job Dissatisfaction	0.017	-0.043	-0.096	-0.326	-0.095
Ability-On-the-job learning x Opportunity → Job Dissatisfaction	-0.213	-0.223	0.235	-0.347	-0.006
Motivation-Learning approach x Opportunity → Job Dissatisfaction	0.262	-0.082	-0.087	-0.122	-0.001

Table S7. path coefficients (multiplicative model) for each segment

Mean absolute error (MAE) and root mean square error (RMSE) can be used to compare predictive capacity. The lower the RMSE or MAE, the better the predictive capacity. When the error distribution is asymmetric or does not follow a normal distribution, it is preferable to use MAE (Hair Jr. et al., 2019). In our case, as shown in Figure S1, it is advisable to use MAE as the criterion for predictive capacity.

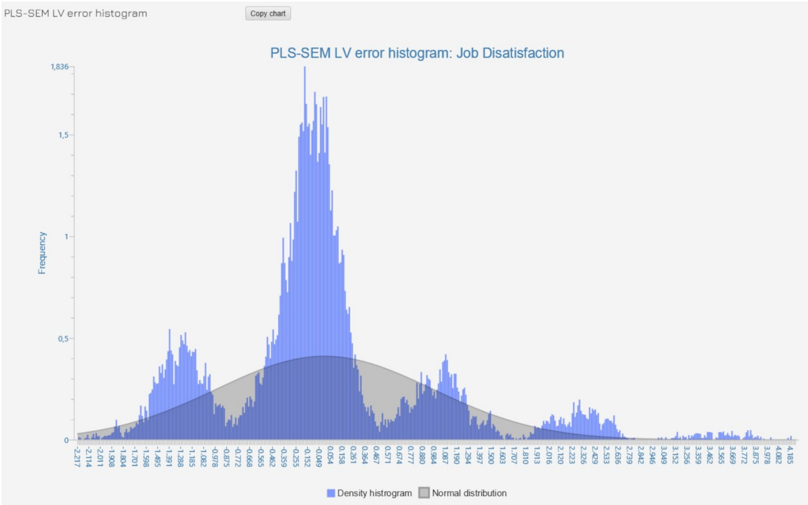

Figure S1. PLS-SEM error distribution