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REGULAR ARTICLE

Identifying employee engagement drivers using multilayer perceptron classifier and sensitivity analysis

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Abstract
Employee engagement is increasingly important, as it can become a competitive advantage for companies, helping them increase productivity, attract talent and improve customer satisfaction. Numerous works have studied the drivers that encourage employee engagement and have developed models to identify them. However, the existing models have limitations, and the literature demands more research on the subject since the precision of the models still needs to improve. This paper presents a computational model that can estimate the drivers of employee engagement accurately. A sample of 205 Spanish employees was used, allowing us to consider a wide sectorial heterogeneity. Different methods have been applied to the sample under study to achieve a high-precision model, selecting drivers using the Multilayer Perceptron Classifier and quantifying the impact of the drivers with Sensitivity Analysis. The results obtained in this research present important implications for the managerial improvement of human resources departments by facilitating the design of strategies and policies that foster employee engagement, which significantly influences corporate results.

Keywords Employee engagement · Multilayer perceptron · Competitive advantage · Sensitivity analysis

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1 Introduction

The world has experienced a sociotechnical revolution called Industry 4.0, significantly impacting organizations´ tangible and intangible resources. Ravina-Ripoll et al. (2019) describe the Industry 4.0 era as marked by governance systems that progressively undermine the Welfare State while adopting business management models characterized by precarious employment and significant job reductions. Furthermore, this era comprises disruptive technologies that have triggered unprecedented changes in the organization of work (Ghobakhloo, 2018), altering how employees interact and engage in their work environment (Tortorella et al., 2021). Industry 4.0 enables more precise methods for data collection and analysis. The availability and access to improved information promote a learning environment that can directly affect employee involvement (Mrugalska & Wyrwicka, 2017). Therefore, the more organizations reinforce these involvement practices, the more likely they are to achieve more favourable outcomes, including higher employee satisfaction, greater engagement, improved quality of work life, and enhanced corporate performance (Tortorella et al., 2021). In this context, companies should develop their human resources to ensure long-term competitiveness as the optimal strategy (Guerci et al., 2019). To do so, employee engagement (EE) is crucial as it has been proved to significantly impact corporate results (Chandni & Rahman, 2020).

For more than three decades, building EE has generated significant interest among organizational practitioners and academics (Martinescu et al., 2022; Mackay et al., 2017). This popularity is due, in large part, to the link between EE, job performance and organizational success (Kilroy et al., 2022; Rich et al., 2010; Xanthopoulou et al., 2009). EE is a positive and fulfilling work-related mental state defined by vigour, dedication, and absorption. Most human resources professionals consider them to be the pillars of a high-performance workforce (Schaufeli et al., 2002).

Since EE significantly impacts corporate results, anticipating or controlling EE behaviour is essential for companies (Chandni & Rahman, 2020). For this reason, professionals and academics have not been oblivious to the importance of understanding the EE drivers (Gullekson et al., 2021; Kumar, 2021; Mutha & Srivastava, 2023; AlZgool et al., 2020; Yuan et al., 2020; Bakker, 2017; Cole et al., 2012). However, the results obtained differ from one study to another, mainly due to multiple measurement perspectives, the use of different samples and the low level of adjustment of the models used (Cole et al., 2012; Jose & Mampilly, 2014). In this context, the previous literature calls for new research to accurately determine the EE drivers (De la Calle-Durán & Rodríguez-Sánchez, 2021; Galanti, 2021). To cover this gap, this study uses a sample of 205 Spanish employees who work in companies selected from different industries and sizes. With structured questionnaires and corporate information from the employees and companies in the sample, a Multilayer Perceptron model (MLP) has been built to determine EE drivers accurately. MLP is a computational technique with great potential to detect all possible interactions between independent and dependent variables (Chatterjee & Das, 2023; Perez-Campdesuñer et al., 2018; Shahiri et al., 2015). Previous studies have successfully used this technique as an engagement prediction method. For example, Turhan et al. (2016) for students and Ghadati and Sasmok (2019) for teachers. Our results indicate that the MLP model built has an accuracy greater than 91% and provides a unique set of variables with high sensitivity to the EE. The study also presents essential theoretical and managerial implications that favour the knowledge of EE formation.

The rest of the study is organized as follows. After this introduction, a literature review of the factors significant for EE in previous research is presented. Below are the methodological processes and the results obtained. Finally, the main conclusions and suggested future lines of research appear.

2 Literature review and research hypotheses

Kahn's (1990) pioneering study defined EE as individuals investing their physical, cognitive, and emotional energies in performing their job tasks. In this way, committed people are psychologically present, attentive, connected, integrated, and focused on fulfilling their roles. Schaufeli et al. (2002) indicate that EE is a positive cognitive-affective work-related state. In this sense, EE reflects employees′ level of attachment and loyalty toward their organization and the type of behavioural performance they consistently display to help the organization achieve its goals (Harter et al., 2002). The contemporary definition of commitment has a similar meaning, defining EE as a positive work-related state of mind composed of vigour, dedication, and absorption (Schaufeli et al., 2002). Vigour refers to high energy levels, a willingness to exert effort, and persistence in work-related tasks. Dedication involves feelings of involvement in one's work and experiences of enthusiasm, inspiration, pride, and challenge. Finally, absorption is characterized by total concentration, immersion, and deep engagement in one's work, where time passes quickly and it becomes difficult to detach from work.

EE has become an increasingly prominent area of study among professionals and academics in business management (Verčič & Vokić, 2017). Organizations embrace EE in stakeholder interactions to secure a sustainable competitive edge (Pansari & Kumar, 2017). In this context, businesses seek to generate value through their participation and the cost reductions that result from enhanced engagement (Kumar & Pansari, 2016). As such, EE is crucial for improving organizational performance (Menguc et al., 2017). EE consistently contributes extra effort to their tasks, a critical competitive advantage for organizations (Harter et al., 2016). EE also demonstrate greater trust in their leaders and are more adaptable in complex work scenarios (Van Allen, 2013). In contrast, disengaged workforces represent a global challenge with significant financial costs (Martinescu et al., 2022; Harter et al., 2010).

EE drivers are typically found in work environments that offer social support, performance feedback, autonomy, learning opportunities, and varied tasks (Christian et al., 2021). High levels of EE are fostered in such environments because they help employees fulfil basic psychological needs for autonomy, connection, and competence (Deci & Ryan, 1985). According to the Job Demands-Resources model (Schaufeli & Bakker, 2004), social support and feedback are critical drivers of EE. An individual can sustain high levels of engagement only when the resources provided exceed the job demands (Cole et al., 2012). Bakker (2017) identifies two approaches to promoting EE. One approach involves top-down strategies, where organizations implement human resource management systems to support EE. The other proactive approach focuses on self-management, personal growth, leveraging individual strengths, and utilizing available resources. Both human resource management practices and leadership initiatives play a significant role in fostering EE by creating a supportive work environment. However, employees also contribute to their engagement by adopting proactive behaviours. Overall, organizations that provide clear strategies for offering resources to employees, combined with employees who actively engage in behaviours like work preparation and resource utilization, are more likely to experience higher levels of EE.

Although the study of EE drivers has been investigated to some extent in the previous literature, existing research yields different results, partly due to variations in how EE is measured and manifested between samples and studies (Cole, 2012). Furthermore, most of these studies have addressed only the effect of specific EE drivers, with no empirical cases considering a set of drivers from a global perspective. For example, Jose and Mampilly (2014) attempt to predict EE through dimensions of psychological empowerment. The study is based on primary data collected from 101 employees in three service organizations in central Kerala. Using Multiple Regression, they revealed a positive association between psychological empowerment and EE. Their regression model achieved a fit of 72%. Kavyashree and Kulenur (2023) and Shelke and Shaikh (2023), using samples of workers from India, also indicated that psychological factors such as cooperative work environment, supervisor support, and workplace happiness positively mediate EE. On the other hand, Singh (2017) concluded that job satisfaction leads to a higher EE. In a study with 224 respondents from an industrial organization, Multiple Regression techniques were applied to obtain an estimation precision of 45%. Linggiallo et al. (2021) showed that personality and job satisfaction positively and significantly affect EE. Their study used a survey of 167 Indonesian employees and Structure Equation Modeling techniques and achieved an adjustment of 66%. Pieters (2018) investigated the dimensions of organizational justice that affect EE among Namibian bank employees. Using a cross-sectional survey design, she concluded that the significant EE drivers were organizational justice and intrinsic job satisfaction. They used Multiple Regression and achieved an accuracy of only 36%. Likewise, Bui and Le (2023) and Sofiyanti and Najmudin (2023) have found a positive effect of organisational culture level on EE.

For their part, Sibiya et al. (2014) addressed the EE drivers through demographic variables of a large information technology organization in South Africa. Using a sample of 2,276 participants and the Utrecht Work Engagement Scale (UWES) to measure EE, they confirmed the relevance of age and job seniority. However, their Multiple Regression model only achieved a fit of 26.1%. Also, Acuña et al. (2021), using a sample of Chilean workers, show differences by gender and age.

Other studies have confirmed the link between corporate social responsibility and EE. For example, Gullekson et al. (2021) (with Regression Analysis and adjustment of 62.19%) and Nazir and Islam (2020) (with Structure Equation Modeling and adjustment of 55%) found that employee perceptions of their organization's corporate social responsibility are positively related to EE. Still, the extent of this relationship may vary between different regions and cultural values. Likewise, Afsar et al. (2020) investigated the effect of the perception of corporate social responsibility on

EE through work meaningfulness. Using data from employees working in various industries in Pakistan, they found that perceptions of corporate social responsibility had the most potent positive effect on EE through work meaningfulness among employees with stronger incremental moral beliefs and moral identity centrality weaker. Their analysis achieved an accuracy of 42% by applying Structure Equation Modeling. Recently, Jiang and Luo (2024) and Koeswayo et al. (2024) have confirmed that corporate social responsibility and reputation are positively and significantly associated with EE.

Using Structural Equation Modeling, Alzgool et al. (2020) analyzed bank employees in Bahrain to highlight the significance of leaders' emotional intelligence in fostering EE. The results supported the proposed mediation hypotheses, showing that self-efficacy and resilience significantly mediated the link between leaders' emotional intelligence and EE, with an estimated adjustment of 69.3%. Similarly, Mutha and Srivastava (2023) demonstrated that leaders are critical in promoting EE within virtual environments. Their findings underscored the importance of trust among team members, particularly in how it influences the relationship between effective leadership communication and EE, with a 52.4% adjustment. Additionally, Kandil and Moustafa (2021) explored the impact of virtual leadership practices on EE, finding that certain leadership practices in virtual settings significantly affected EE. In their study, they applied Regression Analysis and only achieved an adjustment of 36.1%. For their part, Quek et al. (2021) investigated how leadership influences EE among direct care nursing staff at a large UK hospital. One hundred sixteen direct-care nursing workers were sampled using a mixed methods explanatory sequential design. Subsequently, a maximum variance sample of 15 participants was interviewed to understand the motivations and attitudes influencing employee outcomes through distributed leadership. Their results obtained an accuracy of 32.4%. Alam et al. (2023) used a sample of employees in the North American energy industry and found that transformational leadership was one of the EE´s most predictive factors. Recently, Giallouros et al. (2024) used a sample of public health employees in Cyprus. With a Structure Equation Modeling, they found that factors such as leadership role encouragement and employee-oriented leadership could lead to higher EE by facilitating better job resources.

Employees and their social environment have also been indicated as EE drivers. Previous studies have revealed the positive effects of physical activity on EE, confirming that non-sedentary people are more committed to their employment goals (Gil-Beltran et al., 2020; Nishi et al., 2017). Likewise, Yuan et al. (2020) approached returning to work as an essential antecedent of the EE who return to work during a pandemic period. Collecting data from Chinese workers, their results link EE with job withdrawal, use of personal protective equipment, and task performance to underscore the downstream implications of a return to work. Similarly, Khan (2021) has developed a model that explains how misinformation on social media triggers employee anxiety, which affects his EE. Meynaar et al. (2021) studied burnout and its association with EE among Dutch employees. Using an online questionnaire, they found that burnout was negatively associated with EE. Tulucu et al. (2022), collecting data from 164 nurses in Cyprus, found that mindfulness significantly increased EE and that resilience positively mediated this relationship. Also, Galanti et al. (2021)

investigated the impact of work-family conflict, social isolation, work autonomy, and self-leadership on productivity and EE. Using an online questionnaire completed by 209 employees, they determined that work-related conflict and family and social isolation of employees were negatively related to EE. At the same time, self-leadership and autonomy were positively correlated. However, the fit level of their Linear Regression model did not exceed 47%.

Other recent studies that have tried to determine the factors that explain a higher EE have been conducted only from a theoretical perspective. Notable among them are the works of Kumar (2021) and De la Calle and Rodríguez (2021). Kumar (2021) outlined a set of crucial variables that HR managers can use to enhance EE, suggesting five critical elements: value, voice, variety, virtue, and vision. Similarly, De la Calle and Rodríguez (2021) identified the primary drivers of EE that contribute to employee well-being in the current work environment. Through a literature review, they proposed a theoretical model based on the 5Cs framework to strengthen EE. The key drivers in their model are conciliation, cultivation, trust, compensation, and communication.

According to the analysis of previous literature, we have confirmed that the methods used to identify EE drivers have been statistical techniques such as Regression Analysis and Structure Equation Modeling. Secondly, the models developed with these statistical techniques have yet to reach high levels of precision since they are located between 26.1% and 72.0%. For example, using Regression Analysis, the highest levels of precision were those achieved by Gullekson et al. (2021) and Jose and Mampilly (2014), with adjustment rates of 62.1% and 72.0%, respectively. For its part, applying Structure Equation Modeling, the highest adjustment rates were obtained by Linggiallo et al. (2021) and Alzgool et al. (2020), with 66.0% and 69.3%, respectively.

On the other hand, we know that computational techniques have great potential to detect all possible interactions between independent and dependent variables (Chatterjee & Das, 2023; Perez-Campdesuñer et al., 2018). Previous studies have successfully used this technique as an engagement prediction method, although in the context of students (Turhan et al., 2016) and teachers (Ghadati & Sasmok, 2019). Also, computational techniques can process information and discover patterns without the need for prior assumptions about the data distribution (Nuñez de Castro & Von Zuben, 1998). Therefore, we wish to investigate whether methods that do not require assumptions about the underlying model, such as computational techniques, can robustly identify EE drivers. Consequently, we formulate our first research hypothesis as follows:

Hypothesis 1 (H1): Using computational techniques allows the development of a model that accurately identifies EE drivers.

We have also verified that previous studies on EE have tried to identify the factors that can influence EE only partially since most of these studies have addressed the isolated effect of specific characteristics. Thus, and focusing only on psychological variables, Jose and Mampilly (2014) attempt to predict EE through empowerment, Singh (2017) and Pieters (2018) with job satisfaction, and Linggiallo et al. (2021)

with characteristics of personality. Bui and Le (2023) and Sofiyanti and Najmudin (2023) use the level of organisational culture. Giallouros et al. (2024) through the leadership role. Focusing only on demographic variables highlights the studies by Sibiya et al. (2014), Acuña et al. (2021), and Alam et al. (2023).

For their part, Gullekson et al. (2021), Nazir and Islam (2020), Afsar et al. (2020), Jiang and Luo (2024) and Koeswayo et al. (2024) verified the effect of corporate social responsibility perceived by employees and corporate reputation. Focusing on the employees´ conditions, Gil-Beltran et al. (2020) and Nishi et al. (2017) analysed the significance of physical activity, Tulucu et al. (2022) of mindfulness, and Galanti et al. (2021) of work-family conflict, social isolation, work autonomy, and self-leadership.

Given the diversity of EE drivers that have shown some significance in the previous literature (Kavyashree & Kulenur, 2023; Acuña et al., 2021; Linggiallo et al., 2021; Jiang & Luo, 2024; Alam et al., 2023) but always in studies that have measured their isolated effect and have obtained precision levels susceptible to improvement (Gullekson et al., 2021; Linggiallo et al., 2021; Alzgool et al., 2020), we wish to verify if by grouping these factors and testing them in a jointly, it is possible to determine a robust set of variables that can predict EE accurately and consistently. To this end, we have established our second research hypothesis, postulating that:

Hypothesis 2 (H2): There is a specific set of variables that robustly explain EE levels.

3 Methods

The present study applies MLP, one of the widespread examples of computational methodology. Nuñez de Castro and Von Zuben (1998) verified that learning in MLP is a particular case of functional approach, in which no assumption is required about the underlying model of the analysed data. Furthermore, Hetch-Nielsen (1990) demonstrated that an architecture similar to MLP can approximate any function, eliminating the need to employ more complex neural networks. In MLP, the initial processing elements are prearranged in a unidirectional manner. In these networks, the evolution of information occurs based on communications between three types of coincident layers: input, hidden, and output. The networks between these layers are associated with some weighting values and can perform two functions in each MLP node: addition and activation (Ojha et al., 2017). The weights W are adjusted based on the information from the sample set, considering that both the architecture and network connections are known. The objective is to obtain those weights that minimize the learning error. Given, then, a set of pairs of learning patterns $\{(x_1,y_1), (x_2,y_2)\ldots (x_p,y_p)\}$ and an error function ε (W, X, Y), the training process implies the search for the set of weights that minimizes the learning error $E(W)$ (Shang & Wah, 1996), according to the Eq. 1.

$$min_w E(W) = min_w \sum {}_{i=1}^{p} E(W) \tag{1}$$

We use sensitivity, specificity and Matthews's coefficient as quality parameters for the MLP model. Sensitivity assessed the model's ability to identify high EE cases accurately. A high sensitivity value indicates that the model correctly classified most workers as high EE when they were. The sensitivity in a binary classification model is calculated using Eq. 2.

$$Sens = \frac{TP}{TP + FN} \tag{2}$$

where TP represents the number of correctly identified high EE workers, while FN represents the number of incorrectly classified high EE workers.

On the other hand, the specificity measures the model´s ability to identify workers with low EE correctly. The specificity is calculated using Eq. 3.

$$Spec = \frac{TN}{TN + FP} \tag{3}$$

where TN refers to the number of workers correctly classified as low EE, while FP is the number of workers incorrectly classified as high EE.

Therefore, it is critical to use sensitivity and specificity to assess the performance of the MLP model properly. Both values should be high and as close as possible. In addition, we use a third quality parameter, the Matthews coefficient, to facilitate the evaluation of the models. This coefficient varies as a function of sensitivity and specificity, decreasing when these values distance themselves. An overconfident MLP, classifying most cases as high EE, will show low sensitivity (it will classify workers with low EE as high EE) and high specificity. This would negatively affect the Matthews coefficient, showing a low value due to the imbalance in sensitivity and specificity values. Therefore, the Matthews coefficient shows high values when sensitivity and specificity are tall and have similar values. The calculation of this coefficient is carried out using Eq. 4.

$$MCC = \frac{(TP \cdot TN - FP \cdot FN)}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}} \tag{4}$$

In a complementary way, and to obtain information about the importance of each variable in the prediction model, a Sensitivity Analysis has been applied (Ramchoun et al., 2016; Yang et al., 2008). This analysis consists of taking 100% of the data and dividing it into groups. Each data group is processed in the MLP developed as many times as there are variables in the model. For this purpose, a zero value is placed as soon as the value of one of the variables changes. This can be done because the network evaluates its responses against already known ranking values, according to Eq. 5.

$$Sx_i = \sum_{j=1}^{n} (\Phi\, x_{ij}\,(o) - \Phi\, x_{ij})^2 \tag{5}$$

where $\Phi x_{ij}(0)$ is the MLP's output value when variable X_i is zero, Φx_{ij} is the known classification value, X_i is the significant variable, and Sx_i is each variable's sensitivity analysis result.

4 Sample and variables

We used data from a random sample of 205 employees of Spanish companies selected according to geographic quota sampling and gender criteria. For the sample to adequately reflect the distribution and characteristics of the population of interest, stratified random sampling techniques have been used. These techniques have included geographic stratification criteria, dividing the population into strata based on regions, ensuring that the proportion of the sample from each geographic area reflects the proportion of that area in the total population. Criteria have also been applied regarding the definition of gender strata, ensuring that the sample is representative of the proportion of genders in the total population. Along with the above, statistical techniques have been used to determine the sample size, which has allowed a sampling error of 6.8% at the 95% confidence level. The participants completed the questionnaires, and to guarantee their anonymity, a strict protocol informed them that their responses would be completely anonymous and that no identifiable personal data would be collected (Gullekson et al., 2021; Dillman et al., 2014).

The interviewees´ profiles were 48.8% women and 51.2% men; 46.4% were technicians, 35.1% were middle managers, and 18.5% held directive positions. Regarding the company´s size, 19.6% were microenterprises, 19.0% were small, 20.0% were medium-sized, and 41.4% were large companies. Regarding work experience, 10.2% were 0–3 years old, 13.7% were 4–10 years old, 38.5% were 11–20, and 37.6% were over 20 years old. The mean age of the respondents is 42.8 years (with a standard deviation of 8.6). The activity with the most significant weight is Manufacturing (30.3%), followed by Commerce (18.5%) and Agriculture (15.1%). Table 1 offers details of the sample´s characteristics.

The information was collected during September and December 2022 from a structured online questionnaire on EE and on the factors that in previous literature have been associated with it as explanatory variables (Afsar et al., 2020; Schaufeli et al., 2006). Thus, together with the EE variable, possible explanatory factors were measured. The sociodemographic variables used were selected from the study by Sibiya et al. (2014) since, when addressing the drivers of EE, they pointed out differences by gender, age, managerial position, and experience. Another group of independent variables, which refers to the company type, was selected from Afsar et al. (2020), who also considered the company size, scope of action, strategy, and industry as possible EE explanatory factors. Additionally, an independent variable that indicates the family nature of the company. This relationship between EE and family business was previously detected in the studies by Uddin et al. (2023) and Ramirez-Lozano et al. (2023). On the other hand, two variables that refer to corporate conditions have been selected. These variables measure both the compensations received by workers (De la Calle and Rodríguez, 2021) and the perception that the worker has of the Corporate Social Responsibility developed by their company (Gullekson et al., 2021; Nazir &

Table 1 Sociodemographic characteristics of the sample

	n	%
Gender		
Women	100	48.8
Men	105	51.2
Position		
Technicians	95	46.4
Middle managers	72	35.1
Directives	38	18.5
Company´s size		
Micro	40	19.6
Small	39	19.0
Medium	41	20.0
Large	84	41.4
Work experience (years)		
0–3	21	10.2
4–10	28	13.7
11–20	79	38.5
> 20	77	37.6
Age (years)		
Mean (standard deviation)	42.8	8.6
Industries´ distribution		
Agriculture	31	15.1
Manufacturing	62	30.3
Construction	26	12.7
Commerce	38	18.5
Transportation	16	7.8
Hospitality	8	3.9
Communications	7	3.4
Real estate	10	4.9
Public administration	7	3.4
Family company		
No	157	76.6
Yes	48	23.4

Islam, 2020). Positive effects on EE are expected from both variables. Finally, two other variables have been included to measure the personal conditions of the workers. Specifically, a variable on the level of physical activity used by Gil-Beltran et al. (2020), and another to measure the employee wellness perception, previously indicated as a driver of EE by De la Calle and Rodríguez (2021). Table 2 summarises the variables used in the research.

The EE measurement tool used in this research was the Utrecht Work Engagement Scale-9 (UWES-9), developed by Schaufeli et al. (2006). This tool contains items grouped into three measurement dimensions (vigour, dedication and absorption). Previous literature has shown that the UWES-9 has acceptable psychometric properties and can be used in studies on organizational behaviour (Um & Ji, 2024). On the other hand, the Compensation was evaluated using a questionnaire that offers considerable validity and reliability advantages, referring to the employees´ perceptions of the equity in their company´s practices concerning internal compensation, external

Table 2 Econometric variables

Variables	Definition	Measure	Source
Dependent variable			
Employee Engagement	Satisfactory cognitive-affective state about the work carried out	Low EE: If the EE level is lower than the sample mean; High EE: If the EE level is higher than the sample mean	Kahn (1990); Harter et al. (2002)
Independent variables			
a) Sociodemographic			
Gender	Employee gender	0: Male; 1: Female	Sibiya et al. (2014)
Age	Employee age	Number of years	
Managerial Position	Job held	1: Technician; 2: Middle management; 3: Directive	
Experience	Seniority in the company	1: 0–3 years; 2: 4–10 years; 3: 11–20 years; 4: >20 years	
b) Company type			
Size	Number of employees	1: Microenterprise (< 10 employees); 2: Small enterprise (< 50 employees); 3: Medium enterprise (< 250 employees); 4: Large enterprise (> 250 employees)	Afsar et al. (2020)
SME	Small and medium enterprise	0: No; 1: Yes	Afsar et al. (2020)
Family	Family business	0: No; 1: Yes	Uddin et al. (2023); Ramirez-Lozano et al. (2023)
Scope	Scope of action	1: Local; 2: Regional; 3: National; 4: International	Afsar et al. (2020)
Strategy	Action plan to achieve strategic objectives	1: Global; 2: Corporate; 3: Business; 4: Operational	Afsar et al. (2020)
Industry	The activity of the company	1: Production; 2: Commerces; 3: Services	Afsar et al. (2020)
c) Corporate conditions			
Compensations	Employee perception about the fairness of the company in compensation	Likert scale, from 0: Low to 5: High	De la Calle and Rodríguez (2021)
Corporate Social Responsability	The moral and ethical obligation of companies in their relations with employees, the environment, society and the economy	Likert scale, from 0: Low to 5: High	Gullekson et al. (2021); Nazir and Islam (2020)
d) Personal conditions			
Physical Activity	Employee physical activity level	1: Low; 2: Moderate; 3: High	Gil-Beltran et al. (2020)
Wellness	Employee wellness perception	0: Low; 1: High	De la Calle and Rodríguez (2021)

compensation and benefits (Milkovich & Newman, 2005). Corporate Social Responsibility was measured through a questionnaire that refers to the social, economic and environmental dimensions adopted from the previous literature on corporate social responsibility and EE (Afsar et al., 2020; Bansal, 2005). This questionnaire has also demonstrated consistency and reliability in previous related to corporate social responsibility and EE (Farrukh et al., 2020). In turn, the International Physical Activity Questionnaire (IPAQ) in its reduced version (IPAQ-SF) was used to measure employees´ Physical Activity level. This measure provides acceptable levels of reliability to evaluate both activity status and sedentary lifestyle (Brown, 2004). Finally, Wellness was captured through the Perceived Wellness Survey, which comprises emotional, intellectual, physical, social, occupational and spiritual dimensions and offers validity and high reliability (Adams, 1997).

5 Empirical results

This study needed to identify EE drivers. For this, information from the 205 employees described in the sample was processed, dividing the sample into three subgroups. The first subgroup, comprising 60% of the cases studied, was used for training. The second subgroup, including 25% of the cases, was used as a validation set for the early stop condition. The third group, comprised of the remaining 15% of cases, was used as a test group to verify the generalizability of MLP.

The model comprises an input layer in which as many neurons as independent variables have been considered in the research (14 variables). For its part, the hidden layer can be formed a priori by any number of neurons. We have optimized the number of neurons in the hidden layer experimentally, training 20 MLPs for each number of neurons in this layer, starting with a single neuron and ending the experiment with 50 neurons. Thus, 1,000 MLPs were trained, and the results were compared to choose the optimal number of neurons in the hidden layer. Figures 1 and 2 show the variation of the quality parameters according to the number of hidden layer neurons in the

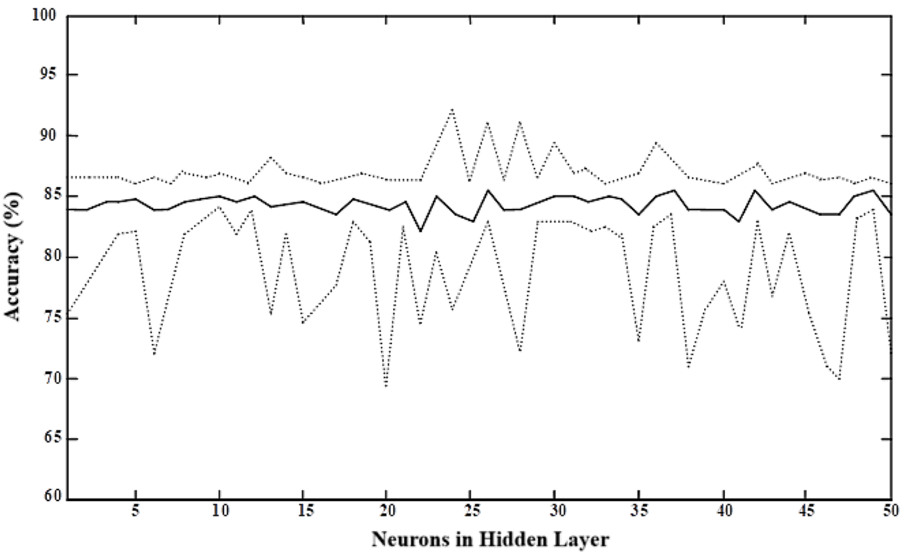

Fig. 1 Relationship between MLP accuracy and neuron number in the hidden layer. The X-axis represents the neuron number in the hidden layer, the Y-axis indicates the MLP accuracy percentage, and each point represents the maximum and minimum accuracy values obtained

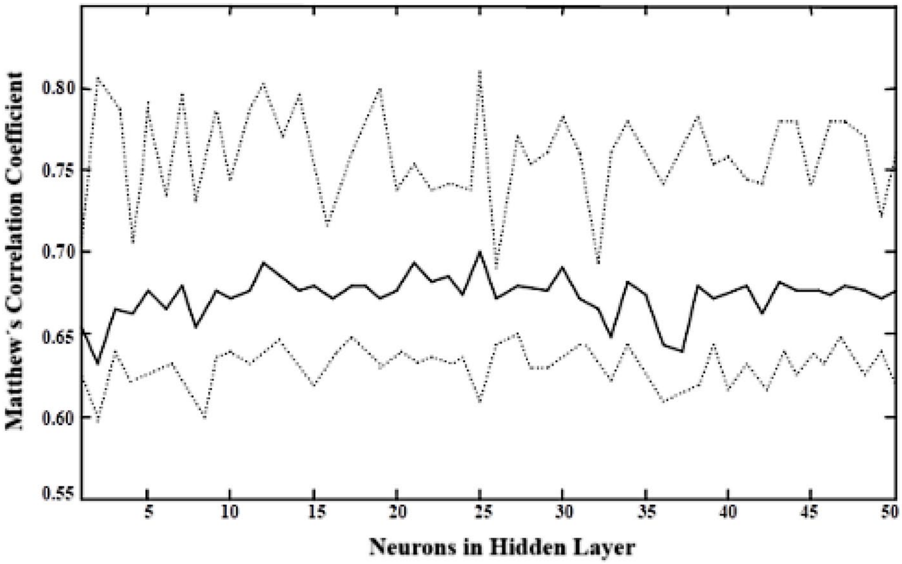

Fig. 2 Matthews' coefficient in the function of neuron number in the hidden layer. The X-axis represents the neuron number in the hidden layer, the Y-axis indicates the Matthews' coefficient values, and each point represents the maximum and minimum Matthews' coefficient obtained in the experiment for the best-trained network

Table 3 Classification matrix of the training set for MLP

Prediction			
Current group	Number of obs.	High EE	Low EE
High EE	123	119	4
Low EE	123	14	109

Total percentage of correctly classified observations: 92.69%

experiment for the best-trained network. Finally, the output layer of the MLP consists of a single neuron, which is activated to predict high EE or low EE using a hyperbolic tangent sigmoid function.

During the training phase, adjustments were made to the weights of all neurons using the conjugate gradient backpropagation algorithm. An early stop condition was established to achieve a minimum gradient, considering between 1 and 5 or more than six consecutive errors. For the learning process, the gradient descent function was chosen to update the weights and biases, and the root mean square error function was used to measure performance.

The results obtained with the MLP model proposed in this study are presented below. Tables 3 and 4 show the results achieved with the training and test data sets, respectively. With training data, the accuracy percentage reached is 92.69%, and with test data, 91.28%.

For its part, Table 5 shows the results of the MLP model generalization, with the quality parameters: sensitivity, specificity and Matthews coefficient. The results confirm that the best-observed threshold value was 0.47, and the precision achieved ranges from 92.69 to 91.28%. Consequently, our hypothesis H1, which postulated

Table 4 Classification matrix of the testing set for MLP

Total percentage of correctly classified observations: 91.28%

Prediction			
Current group	Number of obs.	High EE	Low EE
High EE	31	30	1
Low EE	31	4	27

Table 5 MLP results

	Training	Validation	Testing
Accuracy	92.69%	91.33%	91.28%
Sensitivity	96.85%	96.01%	97.32%
Specificity	88.58%	86.69%	85.34%
Matthews Coeff.	0.856	0.832	0.832

Table 6 Driver importance

	Importance	Normalized importance
Industry	0.024	11.82
Size	0.039	19.21
SME	0.042	20.69
Family	0.062	30.54
Scope	0.068	33.49
Managerial Position	0.020	9.85
Experience	0.051	25.12
Gender	0.031	15.27
Age	0.026	12.81
Strategy	0.133	65.51
Compensations	0.201	99.01
CSR	0.203	100.0
Wellness	0.061	30.04
Physical Activity	0.037	18.23

whether using computational techniques allows the development of a model that accurately identifies EE drivers, can be accepted.

Finally, the drivers sensitivity analysis results appear in Table 6; Fig. 3. The importance of a driver is a measure of the changes in the predictive value of MLP for different driver values. For its part, the normalized importance is divided by the most important values and expressed in percentages. The drivers with the highest sensitivity in the MLP model are Corporate Social Responsibility (CSR), Compensations, and Strategy, with normalized importance greater than 65%. Other drivers have also shown high sensitivity. Such is the case of Family, Scope, and Wellness, with a relative importance of more than 30%. Therefore, our research hypothesis H2, about whether a specific set of variables robustly explain EE levels, has also been accepted.

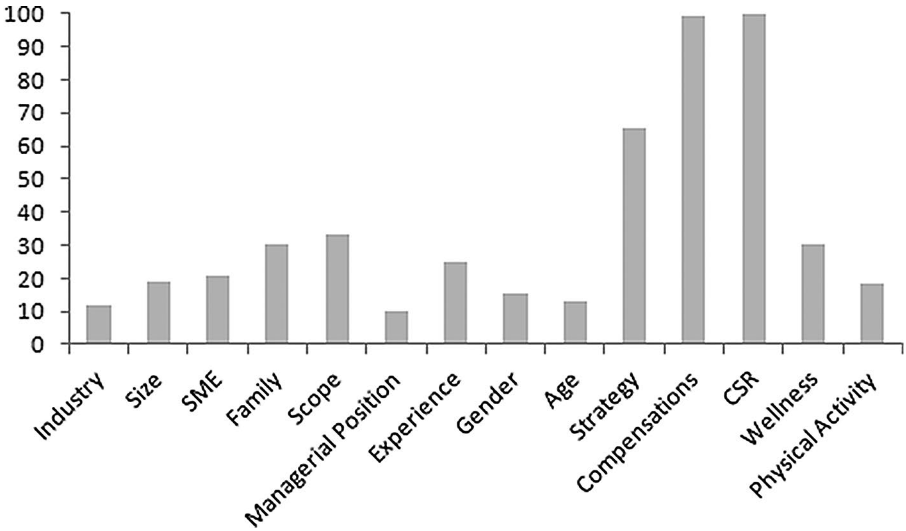

Fig. 3 Impact of drivers on employee engagement. The X-axis identifies each driver, and the Y-axis indicates their normalized importance percentage concerning high employee engagement

6 Discussion

EE is a crucial issue for organizations, and recent studies have identified various factors associated with more excellent EE. Although empirical support for determining these factors is increasing, only some studies have explored EE using a broad set of variables. As a result, it still needs to be determined which set of variables explains the level of EE with high precision. This study aims to help fill that gap by using computational techniques and robustly demonstrate which factors significantly influence higher levels of EE.

Using computational techniques, the MLP model developed has presented a great goodness-of-fit since it has achieved more than 91.0% accuracy in identifying the EE drivers. These adjustment results exceed those obtained by the previous literature which obtained a goodness-of-fit within the range of 26.1 −72.0%. For example, using Multiple Regression Analysis, Sibiya et al. (2014) reached 26.1%, Pieters (2018) 36.0%, Moustafa (2021) 36.1%, Singh (2017) 45.0%, Gullekson et al. (2021) 62.1%, and Jose and Mampilly (2014) 72.0%. With Structure Equation Modeling techniques, Mutha and Srivastava (2023) barely exceeded 52%, Nazir and Islam (2020) 55%, Linggiallo et al. (2021) 66%, and Alzgool et al. (2020) 69%. The high adjustment of our MLP model may reveal the advantages of some computational techniques in solving problems regardless of their complexity, not requiring a linear relationship as other statistical models do.

On the other hand, the results have identified unique drivers´ set with a significant impact on EE. These variables are Corporate Social Responsibility (Normalized importance = 100.00), Compensations (Normalized importance = 99.01), Strategy (Normalized importance = 65.51), Family (Normalized importance = 30.54), Scope (Normalized importance = 33.49), and Wellness (Normalized importance = 30.04).

Previous studies have indicated some of these variables are significant to EE. For example, Gullekson et al. (2021), in the context of workers from an organization that is part of the US health system, and Nazir and Islam (2020), using a sample of 350 employees of luxury hotels in India, also found a positive effect of corporate social responsibility on EE. In this sense, the present study offers empirical support to previous studies conducted in several countries and industrial settings. It could further expand the body of scholarship on the importance of Corporate Social Responsibility in the EE context.

Likewise, this study has identified the Compensation variable as an essential driver in promoting EE. De la Calle-Durán and Rodríguez-Sánchez (2021) obtained similar conclusions. Compensation, which usually involves a monetary payment, rewards a service or job to the person who performs it (Panteli & Sockalingam, 2005). Therefore, planning and implementing a reward policy in any work scenario is essential. Perhaps pay equity is a generic concept and does not imply a specific sum since each employee estimates a fair salary based on their abilities, experience and risk. If it does not match the compensation paid by the company, it could generate a feeling of injustice that would reduce your level of EE.

Regarding sociodemographic variables, our results have confirmed the significance of the Strategy, Family, and Scope variables. Previous studies have also pointed out the impact of sociodemographic variables on EE. However, our results have discovered specific drivers that were not previously indicated. Sibiya et al. (2014) addressed the firm age as an EE driver from a large information technology organization in South Africa. Acuña et al. (2021), using a sample of Chilean workers, show differences by gender and age. Perhaps the different economic and cultural contexts show the existence of regional heterogeneity, which makes the impact of sociodemographic variables on EE different (Saari et al., 2017).

Also, the Wellness variable is of particular importance in our study. With this, we contribute to the literature by validating that employee well-being offers a genuine resource to improve EE. Therefore, work contexts in which employees find meaning in what they do can lead to a higher level of EE. These results align with those obtained by Linggiallo et al. (2021), using a sample of 167 employees from Indonesia and those of Singh (2017) about employees of electrical appliances manufacturing organizations from India. They also found that the perception of wellness leads to a higher EE. Consequently, it seems acceptable that passionate employees use their full potential, show more commitment to their organization, and have no desire to leave. Even with the above, these previous studies could only point out the importance of employee well-being as an isolated variable rather than as part of a set with a high relationship with EE, as is the case of the present study. Still, the results suggest that to achieve high EE, companies should focus on facilitating working conditions so that employees can balance work and family life. Likewise they understand that understanding employees' expectations and plans, and not just monetary payments, is an opportunity to improve organizational engagement.

Finally, other variables related to the activity and the size of the company (Industry, Size, SME) and specific characteristics of the employees (Managerial Position, Experience, Age, and Physical Activity) have not been shown in our study as significant sensitivity to explain EE levels. These results differ from those obtained by

Sibiya et al. (2014) and Acuña et al. (2021) for employees from South Africa and Chile, respectively. They revealed the importance of age and experience. Still, the extent of this relationship may vary between different regions and cultural values, as Gullekson et al. (2021) pointed out. They are also different from those obtained by Gil-Beltran et al. (2020) and Nishi et al. (2017) regarding the influence of physical activity on EE, an extreme that has not been confirmed in our research.

7 Conclusions

This study aimed to identify the EE drivers using a high accuracy analysis model. Data was collected using structured surveys and corporate information from 205 Spanish firms. According to the MLP model results, it can be concluded that the EE drivers are related to the employee´s perceptions of their wellness, the equity of compensation, the company´s ethical behaviour, the action plan to achieve the strategic objectives, the family character and its scope of action. These drivers make up a unique set that shows a high relationship with the EE. Consequently, managers must pay special attention to these variables to achieve a sustainable competitive advantage that improves their corporation´s performance. In the same way, other variables such as the activity, the size of the company and specific characteristics of the employees, such as their managerial position, experience, gender, age, and physical activity, do not show a significant relationship with the EE.

The application of computational techniques, like those considered by the study, is feasible from the technical and economic points of view for analysing organizations. It can be another tool for managers to monitor EE and identify employees with behavioural qualities to improve their organization´s performance. Once the people in the organization who may be susceptible to excellent EE have been identified, managers can design appropriate action plans to achieve strategic objectives, paying particular attention to the scope of action, their compensation policy and the area of corporate social responsibility. In the same way, considering that the family nature of organizations favours the EE, any action aimed at selecting generational replacement protocols in the management of companies could be regarded as, in addition to a guarantee for investors and creditors, a measure to increase the EE.

While this study aims to address some of the existing gaps and limitations in research on EE drivers, it also has its constraints that should be acknowledged and suggests areas for future investigation. First, this research may have incurred response bias, like many studies using self-reported data. Participants may have offered biased estimates due to a misunderstanding of what an appropriate measurement is or even due to social desirability bias. Therefore, it would be interesting for future studies to apply techniques that control for response bias, for example, validating the results with additional sources or conducting follow-up surveys to confirm initial results. A second limitation of the current research is that the information obtained was collected in a specific period and could not examine whether possible variations in the mood and behaviour of the participants throughout the seasons of the year could have introduced biases in data collection. Therefore, new studies could approach the measurement of EE and its drivers by considering different times of the year to obtain a more complete and balanced view of the participants' opinions. Notwithstanding the above limitations, the conclusions of the present study have other potential implications for future research. The study could be replicated in various organizations with different fields of action, such as local, national and multinational corporations. It will be interesting to view this study in light of globalization´s increasing effect on the corporation´s strategic objectives. Furthermore, given that the present study assumed a cross-sectional research design in different industries, it would be interesting for future research to delve into the possible differences between sectors and verify whether the factors driving EE show specific sectoral differences.

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Declarations

Ethical and informed consent for data used All those interviewed in this study have participated voluntarily and have expressed their consent.

Competing interests The authors declare not to have financial interests.

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