Improving customer engagement through the determinants of employee engagement: An approach using Radial Basis Function Neural Networks

1. Purpose of the study

Employee engagement (EE) is an issue of growing importance in the literature on business management because it has a significant impact on corporate results, while also affecting relationships and customer engagement (CE) (Chandni & Rahman, 2020). Therefore, anticipating or controlling the behavior of EE has great importance for a company. However, predicting the factors that determine the level of EE is an almost impossible intention due to the number of variables that condition this phenomenon. The objective of this research is to try to identify, through the use of Radial Basis Function Neural Networks, which variables of the organization, associated with its human resources, show a relationship or incidence in the EE.

2. Theoretical background

Engagement is the subject of increasing study by professionals and academics in business management (Verčič & Vokić, 2017), and organizations adopt engagement in their relationships with stakeholders to achieve sustainable competitive advantage (Pansari & Kumar, 2017). In this context, organizations strive to engage not only customers but also employees with the aim of generating benefits through CE and cost savings derived from EE (Kumar & Pansari, 2016). CE generates positive results for organizations (Kumar & Pansari, 2016), a favorable reputation, and higher-quality relationships (Hollebeek, 2011). Additionally, employees are critical in designing customer outcomes (de Mattos et al., 2019). Therefore, the level of EE is an important variable to improve the performance of corporations (Menguc et al., 2017) and significantly affects the level of CE (Kumar & Pansari, 2016).

3. Methodology

Data from a random sample of 205 employees of Spanish companies selected according to geographic quota sampling and gender criteria, with a sampling error of 6.8% and a confidence level of 95%, were analyzed. The employees in the sample completed a questionnaire on EE and the factors that in previous literature have been explanatory variables (Afsar, Al-Ghazali, and Umrani, 2020; Schaufeli, Bakker, and Salanova, 2006). These factors refer to socio-demographic variables (Gender, Age, Managerial Position, Physical Activity, and Experience), type of company (Industry, Size, SME, Family, Scope, Strategy, and Industry), and corporate conditions (Compensations, Corporate Social Responsibility, and Wellness). On the other hand, the present study uses Radial Basis Function Neural Networks (RBFNN) in order to model the behavior of the EE of the selected sample. The RBFNNs were proposed by Moody and Darken (1988) and have been shown to be a good universal approximator for any multivariate continuous function. The RBFNN has inputs x_i, i=1,2,3…n, and outputs $y=F_{rbf}(x)$. Inputs are $x=[x_1, x_2, x_3, \ldots, x_n]^T$ and $R_i(x)$ is the output of the receptive field i^{th} with force denoted by b_i. Assuming n_R receptive fields present in the RBFNN, the output y can be expressed as appears in [1].

$$y = F_{rbf}(x, \Theta) = \sum_{i=1}^{n_R} b_i \, R_i(x) \quad [1]$$

where θ contains the parameters of the receptive field units consisting of the parameters b_i and possibly the parameters of $R_i(x)$. For its part, the weighted average output of the RBFNN can be expressed as it appears in [2].

$$y = F_{rbf}(x, \Theta) = \sum_{i=1}^{n_R} b_i \, R_i(x) \Big/ \sum_{i=1}^{n_R} R_i(x) \quad [2]$$

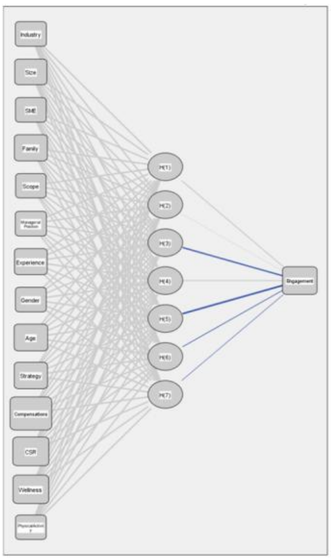
Also, the use of RBFNN, techniques have been applied to measure the importance of the predictor variables (Hunter et al., 2000). To do this, the decrease in network performance and the sensitivities of each predictor variable have been calculated as a function of the proportion of network error when the variable is removed from the model and included. Higher values are indicative of the greater importance of the variable.

4. Main findings

The EE model developed with RBFNN techniques presents a high accuracy with both the training data and the testing data (Table 1). This model consists of 3 layers with 7 neurons in the middle layer (Figure 1). In addition, the analysis of the importance of variables highlights the strong impact that Compensations, Corporate Social Responsibility (CSR), and Wellness have in explaining EE levels, in all cases with an importance greater than 50% (Figure 2).

Table 1. Model summary.

Training		
	Sum of squared errors	56.665
	Relative error	0.798
	Training time	0:00:14.09
Testing		
	Sum of squared errors	29.506
	Relative error	0.825



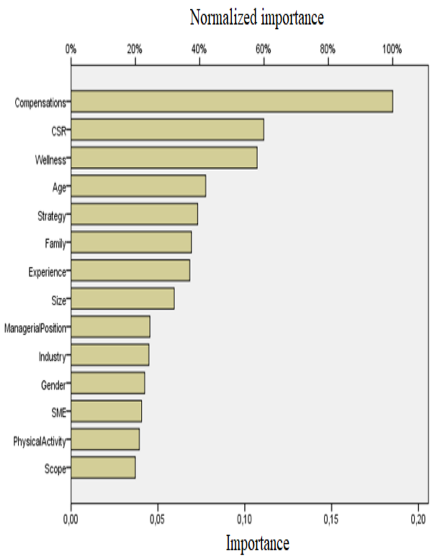


Fig. 1. RBFNN architecture. Fig. 2. Independents variable importance.

5. Contributions

The results indicate that the EE depends mainly on variables that refer to the corporate conditions, specifically to the compensations offered by the companies, the actions in corporate social responsibility, and the levels of wellness perceived by the employees. By modeling with high precision the factors that determine the EE, this study provides significant information on how relationships with stakeholders, and especially the EC, can be improved.

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