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Machine Learning-Based Causality Analysis of Human Resource Practices on Firm Performance

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Abstract: An organization's human resource management practices are essential for its competitive advantage. This study specifically examined human resource (HR) practices that predict corporate performance (employee turnover and firm sales) based on a backpropagation neural network (BPN)-based causality analysis. This study aims to test how to optimize human resource practices to improve organizational performance. This study elucidated the effect of HR practices and organizational-level factors on predicting employee turnover and firm sales. The BPN-based causality analysis revealed the relative importance of explanatory variables on firm performance. To test the model, it employed the Human Capital Corporate Panel open data on Korean companies' HR practices and other characteristics. The analysis identifies causal relationships between specific HR practices and firm performance. The results show that compensation-related HR practices are most influential in predicting firm sales and employee turnover. Moreover, training-related HR practices were modest, and talent acquisition and performance management practices had relatively weak effects on the two outcomes. The study provides insights into how human resource practices can be optimized to improve firm performance and enhance organizational effectiveness. The findings of this study contribute to the growing body of research on the use of machine learning in HR management and suggest practical implications for managers' insights to optimize HR practices.

Keywords: BPN-based causality analysis; firm performance; human corporate capital panel; human resource management; machine learning

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1. Introduction

Human resources (HR) is an important asset in business organizations because, although competitive advantage based on HR cannot be easily achieved, the advantage presents a high barrier to imitation when achieved, enabling firms to sustain their competitive advantages (Barney 1991; Huselid 1995; Becker 1998). Thus, scholars have paid attention to the effect of various HR practices on firm performance. This line of study, strategic HR management (SHRM), has mainly suggested the universal effects of high-performance work systems (HPWSs, a bundle of effective HR practices) on firm-level outcomes, such as turnover rate, labor productivity, innovation, and financial performance.

Meta-analyses have supported the hypothesis that HPWSs positively correlate with firm performance (Subramony 2009). Moreover, SHRM research has observed mediators or moderators between HPWSs and firm performance, such as organizational culture (Chow 2012), organizational communication (Lee et al. 2017), human capital (Jiang et al. 2012), and employee commitment (Takeuchi et al. 2009). Thus, the general suggestion of SHRM is that various HR practices positively affect firms in many aspects, thereby improving organizational effectiveness. Following a previous research stream, this study explored the relationship between HR practices and organizational effectiveness. In particular, it focused on employee turnover and firm sales. In addition, it explored the relative importance and direction of the effects of HR practices in predicting employee turnover and firm sales using machine-learning (ML) techniques. In this respect, this study differs from previous SHRM studies.

First, this study focused on the effect of different groups of HR practices on organizational effectiveness. Previous SHRM studies investigated the effects of HPWSs measured by the aggregated number of implemented HR practices identified as a component of HPWSs (Wright et al. 2005). This approach assumes that all HR practices have a similar effect on a particular outcome, such as employee ability and motivation, and that firms can use different HR practices interchangeably as long as those practices are components of HPWSs. However, each HR practice has different characteristics; thus, the expected effects of each practice on organizational outcomes can differ (Jiang et al. 2012). Therefore, it examined the effect of each group of HR practices, not the aggregated number of HR practices as a whole. HR practices can generally be categorized into talent acquisition, training, development, performance management, and compensation (Combs et al. 2006). Using publicly available data on HR practices and other characteristics of Korean firms (the Human Capital Corporate Panel (HCCP)), this study classified HR practices, which are widely used in Korean firms, into (1) talent acquisition practice, (2) training practice, (3) development practice, (4) performance management practice, (5) compensation practice, and (6) fringe benefits and explored their relative importance in predicting corporate outcomes. This approach enabled us to correctly identify the relative importance of each type of HR practice.

Second, this study explored the complex relationships between each type of HR practice and employee turnover and firm sales using ML techniques. Here, ML, which has been widely introduced into the social sciences, was employed to evaluate the relative importance and direction of the effects of different HR practices. ML can discover patterns from big data and is an information extraction technique that can simultaneously handle a large number of variables (Hastie et al. 2009). A previous study argued that ML should be more widely used in management studies to investigate the unidentified effects of previously known independent variables for theory building (Choudhury et al. 2021). Compared with the regression approach, ML has several advantages in terms of the aims of the present study. Dissimilar to the regression technique, which is frequently used to test the direction of the effect of independent variables predefined by theoretical arguments, ML does not constrain the form of the effects of independent variables on the outcomes. Thus, this technique facilitates the simultaneous discovery of complex relationship patterns between various explanatory and dependent variables. This study is relevant for practitioners and scholars because previous studies suggest that the relationship between a particular HR practice and organizational effectiveness can be nonlinear and highly complex (Yan et al. 2022; Chadwick 2007). Thus, our approach provides practical implications for practitioners building HR systems by introducing and implementing new HR practices and enables scholars to discover new research opportunities.

Third, this study examined the influence of other independent variables at the employee and organizational levels. Although this study aimed to elucidate the influence of HR practices on organizational effectiveness, it included other predictors, such as employee attitudes toward their jobs and organizations, organizational culture, and organizational characteristics, as explanatory variables. Considering that these variables have been recognized as significant predictors of organizational effectiveness, the inclusion helped to understand HR practices' relative importance accurately. Moreover, additional independent variables representing changes inside and outside organizations can provide managers with additional insights into when managers should revise existing HR practices. Changes in demand and technology directly affect organizational effectiveness and require managers to realign HR practices with the change. Thus, understanding the complex relationship between changes inside and outside the organization and organizational effectiveness enables managers to determine when they should revise their HR systems by introducing new HR practices or abolishing existing practices.

Compared with previous SHRM studies, this study has the following two contributions: While previous SHRM studies have tested the effect of bundles of HR practices on organizational performance, this study contributes to examining each effect of HR practices. In addition, unlike regression analysis, which was mainly used in previous studies, ML analysis contributes to understanding complexity by analyzing various organizational variables affecting organizational performance and each HR practice in one model.

This study describes the following three research questions.

Research Questions 1. What are the significant determinants of firm performance (turnover rate, sales)?

Research Question 2. What is the order of importance of HR practices among the determinants of firm performance (turnover rate, sales)?

Research Question 3. What is the pattern of the influence of HR practices on firm performance (turnover rate, sales)?

In summary, this study aimed to understand the effects of HR practices and individual and organizational level factors in predicting employee turnover and firm sales. It investigated the relative importance and direction of the effects of explanatory variables using ML. The rest of this article is organized as follows. The next section reviews the literature, and Section 3 explains the HR data source, independent variables, and characteristics of the integrated dataset. Section 4 discusses the ML process and offers the results. Section 5 discusses the main findings, implications, limitations, and future research directions.

2. Literature Review

Human resource management (HRM) practices have been found to play a crucial role in shaping a firm's performance. While the definition of HRM varies, encompassing aspects like HR department effectiveness, individual practices, or entire systems, a key takeaway from Boselie et al.'s (2005) meta-analysis of 104 studies is that many view HRM as a collection of interconnected HR systems or practices. High-performance work systems (HPWS), for example, bundle practices like recruitment, selection, compensation, training, and job design, positively impact a firm's performance (Gerhart 2007).

Research on HRM systems and firm performance has increasingly explored the mechanisms. This includes how these systems influence a company's financial results and how employees perceive their implementation. Interestingly, even companies using the same HRM system can experience performance variations. This highlights the role of organizational characteristics in shaping how HRM systems function within a company. Further research is needed to fully understand this relationship and the specific mechanisms by which HRM systems ultimately impact performance (Guest 2011).

In addition, research examining the relationship between strategic human resource management and organizational performance is expanding its scope. Ferdousi and Abedin (2023) reported a study on the specificity and performance of human resource management in social business organizations. Compared to other companies, social business organizations have difficulty aligning HRM and organizational goals because they must pursue social and economic goals at the same time. Tortia et al. (2022) discussed the function of HRM for the sustainability of care service businesses targeting nonprofit social enterprises in Italy.

This study takes a universalistic perspective to examine the connection between HPWS and firm performance. The universalistic perspective suggests that there are best practices in HR that can improve performance across different organizations (Delery and Doty 1996). To assess this from a stakeholder viewpoint, we focus on two key stakeholders: shareholders and employees. We use financial performance and employee turnover rate as quantitative measures of success (Guest 1997; Paauwe and Boselie 2005).

According to the resource-based view (Barney 1991), this study argues that HR practices promote excellent human resources in companies and positively affect organizational performance as a competitive advantage factor for companies. The resource-based view provides a theoretical basis for explaining the relationship between HR practices and firm performance (Barney and Wright 1998). According to this theory, a firm's resources and capabilities are critical to its performance and competitive advantage. HR practices, such as recruitment and selection, training and development, and performance management, are essential resources enabling firms to develop and maintain a skilled and motivated workforce. By investing in these practices, human resources are valuable, rare, and not substitutable, which is difficult for competitors to imitate. Therefore, they can be crucial for securing a sustainable competitive advantage (Huselid 1995).

Previous studies found strong evidence that effective HR practices can improve organizational performance. However, they also found that the relationship between HR and performance is complex and that other factors, such as the external environment and organizational culture, can also play a role (Chow 2012). Therefore, this study tests the effectiveness of HR practices in one model, including environmental factors such as strategies, organizational culture, organizational commitment, and organizational trust by ML. Moreover, it explores HR practices that simultaneously satisfy two company-level performances of different attributes by using ML that can be analyzed, including two or more dependent variables in one model. The major outcomes that previous studies have investigated can be categorized into three groups: (1) human resource outcomes (absenteeism rate, turnover rate, individual performance, and team performance), (2) organizational outcomes (productivity and quality of service), and (3) financial outcomes (return on investment and return on assets) (Dyer and Reeves 1995).

Studies applying ML in HRM research are conducted in various research fields, and the studies present the following empirical results. Meddeb et al. (2022) examined the intersection of machine learning and causal knowledge discovery in HRM, highlighting the benefits of incorporating domain experts' causal knowledge. Loyarte-López and García-Olaizola (2022) present an ML-based method for evaluating the internal value of talent and ensuring internal equity in salary criteria, suggesting that ML can support equitable and unbiased salary decisions based on data. Xiang et al. (2022) propose an intelligent HRM system that combines backpropagation neural network and logistic regression analysis to improve effectiveness, which is verified through simulation tests with good practical effects. Vrontis et al. (2022) analyzed 45 HRM field journals using intelligent automation, including artificial intelligence, and explained that automation technologies present a new approach (e.g., technical and ethical level) in the HRM research field. Additionally, these skills are identified as affecting recruitment, training, and work performance in organizations. Furthermore, Garg et al. (2022) analyzed studies using ML technology in HR research. They found that among HR practices, the effectiveness of ML applications was most significant in recruitment and performance management. ML applications improve employee experience and promote employee performance.

3. Data Source and Integrated Dataset

3.1. Overview

This study was conducted using the following steps. First, the study variables were chosen based on previous SHRM studies. The independent variables were classified into HR practices, employee attitudes, and other firm characteristics. All the variables were frequently used in previous studies on the effect of HR practices on employees and performance. Second, the independent variable was generated by extracting information from an HCCP dataset, and then an integrated dataset was constructed. The study variables related to HR practice were composite variables generated using a firm-level dataset. The information for firm characteristics was also extracted from a firm-level dataset. Other variables related to employee attitudes were composite variables based on information from an employee-level dataset. Independent variables at the employee level were aggregated at the firm level. All the study variables were merged using the company identification (ID) and year variable.

3.2. Data Sources

Here, an HCCP dataset was used, which was provided by the Korea Research Institute for Vocational Education and Training (KRIVET). This government-funded institute provides the HCCP dataset to assist studies on changes in HRM activities and their effects on employees and firm performance in Korean firms. The data were collected and distributed biennially since 2005. Data from the 3rd to 7th investigations were used. The HCCP comprises three sub-datasets: firm-level, employee-level, and financial information datasets. The firm-level dataset includes general firm characteristics, perceived environmental characteristics, HR development, and management activities. The employee-level dataset contains data collected directly from employees and includes the demographics of respondents, perceptions about their firms and HR practices, attitudes toward their jobs and firms, and organizational behaviors. The financial dataset provided by KRIVET mainly focuses on accounting-based information, such as sales, assets, debts, and net incomes. Dissimilar to the other two datasets, which are collected biennially, the financial dataset includes annual information provided by the National Information & Credit Evaluation (NICE) information service, a reliable corporate information provider in Korea.

3.3. Variable Selection

To construct the integrated dataset for the present study, variables were generated using three sub-datasets. First, following previous studies (Huselid 1995; Choi et al. 2021; Arthur 1994), employee turnover rate and firm sales were used as the outcome variables. The employee turnover rate was calculated by dividing the number of employees who left the firm by the total number of employees each year. The information for this variable was extracted from the firm-level dataset.

Second, regarding HR practices, eight variables ranging from recruitment to compensation were generated. The HCCP surveyed whether or not a particular HR practice had been implemented in the prior two years. Based on this information, the implemented HR practices were classified into six distinct categories. The categories were based on the general HR process, and classification was guided by a prior study that provides a list of HR practices that are part of HPWSs (Jiang et al. 2012; Posthuma et al. 2013). However, not all listed HR practices were investigated in the HCCP, and thus the number of HR practices used in this study was limited to those investigated in the HCCP. Furthermore, considering compensation level and structure can be an important aspect of HR systems and affect employees' attitudes and behaviors, they were included in the analysis. Specifically, talent acquisition practice is the number of practices used to internally develop or externally acquire high performers. Training practice is the number of practices focused on enhancing the current job performance of employees. Development practice is the number of practices focused on improving the ability and knowledge of employees to enhance future job performance. Performance management practice is the number of practices used to evaluate job performance. Performance-based pay practice is the number of compensation programs based on individual, team, or business-unit performance. Compensation level is the total annual compensation. Compensation structure is the ratio of all performance-based pay to base salary. Fringe benefit is the level of fringe benefits compared with those of other firms in the same industry each year. In addition to HR practices, three variables related to HR departmental activities, such as strategic HR planning and the involvement of the HR department, were also included (Gerhart 2007; Huselid and Becker 1997; Han et al. 2019). Annual HR plan is a binary variable with a value of '1' if a firm sets an annual HR plan or '0' if not. HR plan-strategy alignment is the degree to which a firm's strategy is reflected in its HR activities. HR departmental involvement is the degree to which an HR department engages in corporate strategic planning, a CEO's decision-making, changes in HR practices, and corporate-level innovation. All the variables were extracted from the firm-level dataset except for HR departmental involvement, which was extracted from the employee-level dataset.

Third, to account for the effect of employee attitudes toward their jobs and organizations, organizational culture, commitment, and trust were included in the model. The four aspects of organizational culture were measured using data gathered from the employee-level dataset. Adhocracy culture emphasizes creativity and innovation; clan culture focuses on teamwork and solidarity; hierarchical culture emphasizes rule and process; and market culture focuses on individual capability, competition, and performance. Given that an organization possesses some characteristics of all four cultures, the degree of each type of culture was measured for all firms (Quinn 2011). Organizational commitment was measured as the level of affection for the job, fear of loss, and sense of obligation to stay (Mathieu and Zajac 1990; Meyer et al. 2002). Organizational trust was measured as the level of trust in the management team, other members, and the evaluation and compensation process (Colquitt et al. 2007; Dirks and Ferrin 2001). The information for these variables was extracted from the employee-level dataset.

Finally, six variables related to environmental changes, firm strategy, firm size, and financial condition that could potentially affect firm performance and employee turnover were measured and then included in the analysis. Changes in management environments were measured using the following three variables: changes in the demand for primary products, changes in technologies used in the production process, and changes in the development and introduction of new products. Firm strategy was measured using a binary variable with a value of '1' if a firm focuses on either quality improvement or new product development or '0' if a firm focuses on cost reduction. Firm size was measured by the total number of employees. Leverage was measured by the ratio of total debt to total equity. The first five variables were extracted from the firm-level dataset, and the last variable was extracted from the financial information dataset.

3.4. Data Cleaning and Integrated Dataset

The HCCP performed in 2017 is the 7th investigation, and all the data from the 1st to 7th investigations consisted of 3317 firm–year observations and 74,774 firm–year–employee observations. The first three investigations were excluded from the study because of changes in survey items between the 3rd and 4th investigations, which resulted in the unavailability of information used in the study. In addition, the study sample was limited to manufacturing industries to ensure comparability across the firms in the sample. Thus, the initial sample comprised 1760 firm–year observations and 39,906 firm–year–employee observations from the 3rd and 7th investigations. According to a coding scheme in the HCCP dataset, nonresponse and unknown information are coded −9 and −8, respectively. These values replaced missing values before generating the study variables. This process resulted in the exclusion of 539 firm–year observations (8820 firm–year–employee observations). Thus, the final firm-level dataset comprised 1221 firm–year observations, and the employee-level dataset comprised 31,086 firm–year–employee observations. Finally, the datasets were merged using company ID and year variables. Before merging the firm- and employee-level datasets, the variables generated using the employee-level dataset were averaged by the year–company ID variable. Afterward, the final dataset comprised 25 variables and 1221 firm–year observations.

4. Analysis Process

4.1. Overview

Here, a backpropagation neural network (BPN)-based causality analysis was conducted by using the HCCP dataset (Doh et al. 2016). Data were processed by transforming the scale for each variable with the standardization method before training a model. Thereafter, the regression model with the BPN was generated using the scaled dataset. The BPN-based causality analysis was conducted based on the interconnection weight factors of neurons. All programming and analysis were carried out using TensorFlow based on Python 3 language.

4.2. Data Processing for Training

The data were preprocessed to transform the data scale to generate the artificial neural network (ANN) model (Nawi et al. 2013). In generic data processing, there are two types of data normalization. First, normalization transforms the range of the data as a value between 0 and 1 based on the maximum and minimum values for each variable data. Second, standardization transforms data to produce the mean, 0, and standard deviation, 1, assuming the data follow a standard normal distribution. This method is advantageous as the influence can reduce the relative magnitude between data, increase the accuracy of the model, and be insensitive to outliers. In this study, the data were processed using the standardization method with respect to the input and output data. The standardization is represented in Equation (1). Here, x is the real scale value of the data, μ is the mean of the real scale data, σ is the standard deviation of the real scale data, and z is the z-score (Agarap 2018), indicating the standardized value of the real scale data.

$$z = \frac{x_i - \mu}{\sigma}\ (i = 1 \sim N) \tag{1}$$

Furthermore, the variable relationship to generate the BPN model comprised 23 independent variables relative to HR practices and 2 dependent variables regarding "employee turnover" and "firm sales". These variables are summarized in Table 1.

Table 1. Independent and dependent variables for the BPN model.

	Variables	Type	z-Score [μ, σ]
Independent variables (Input data)	Performance management practice	float	[2.62, 1.68]
	Training practice	float	[3.35, 1.13]
	Development practice	float	[1.75, 1.55]
	Compensation level	float	[44.56, 9.69]
	Organizational Commitment	float	[3.32, 0.33]
	Compensation structure	double	[374.06, 347.01]
	Firm strategy	float	[1.83, 0.69]
	HR plan-strategy alignment	double	[2.56, 0.90]
	Clan culture	float	[3.53, 0.38]
	Change in technology	double	[2.41, 0.78]
	HR plan-strategy alignment	double	[0.76, 0.43]
	Fringe benefits	float	[2.85, 0.83]
	Market culture	float	[3.47, 0.33]
	Performance-based pay practice	float	[1.45, 1.21]
	Change in demand	double	[3.05, 1.04]
	Talent acquisition practice	float	[1.42, 0.72]
	Adhocracy culture	float	[3.30, 0.40]
	Organizational Trust	float	[3.43, 0.38]
	Change in new product	double	[2.29, 0.86]
	Hierarchical culture	float	[3.50, 0.29]
	HR departmental involvement	float	[3.42, 0.41]
	Firm size	float	[639.67, 1282.45]
Dependent variables (Output data)	Leverage	float	[1.64, 19.87]
	Employee turnover	float	[0.14, 0.22]
	Firm sales	double	[485,352,386, 1890,706,117]

4.3. Backpropagation Neural Network Model

ML has been widely used in various fields. Among many ML techniques, ANN is an algorithm inspired by human neural network architectures. An ANN model can be generated using connections between many neurons and layers in a complicated manner regarding structured and unstructured data, such as images, videos, and signal data (Abiodun et al. 2018).

The determination of neural network architectures remains a significant challenge in the field of artificial intelligence. This challenge arises due to the absence of specific guidelines for selecting an optimal architecture. Instead, the choice of architecture, including the number of neurons and hidden layers, relies on experiential knowledge acquired through iterative training processes.

In this study, we conducted a case study aimed at identifying an architecture that avoids overfitting by progressively increasing the number of neurons within a single hidden layer. The decision to choose a single hidden layer was motivated by two primary factors. Firstly, it aimed to streamline the model, simplifying its complexity. Secondly, it facilitated the causality analysis of the relationships between human resource practices (input), turnover, and sales (multi-output) using the interconnected weights in the simplified neural network model.

The generic architecture of the feed-forward neural network comprises terms for the interconnected weight of hidden and output layers (v and w), bias (b), input layer (x), output layer (O_p), and activation function ($\sigma_{\text{act.}}$) in Equation (2).

$$O_{p_i} = \sum_{j=1}^{N_j} w_{jk} \left\{ \sigma_{\text{act.}} \left(y = \sum_{i=1}^{N_i} v_{ij} x_i + b \right) \right\} \tag{2}$$

Here, the architecture of the BPN model comprised an input layer with 23 neurons, a single hidden layer with 4096 neurons, and an output layer with 2 neurons (Figure 1).

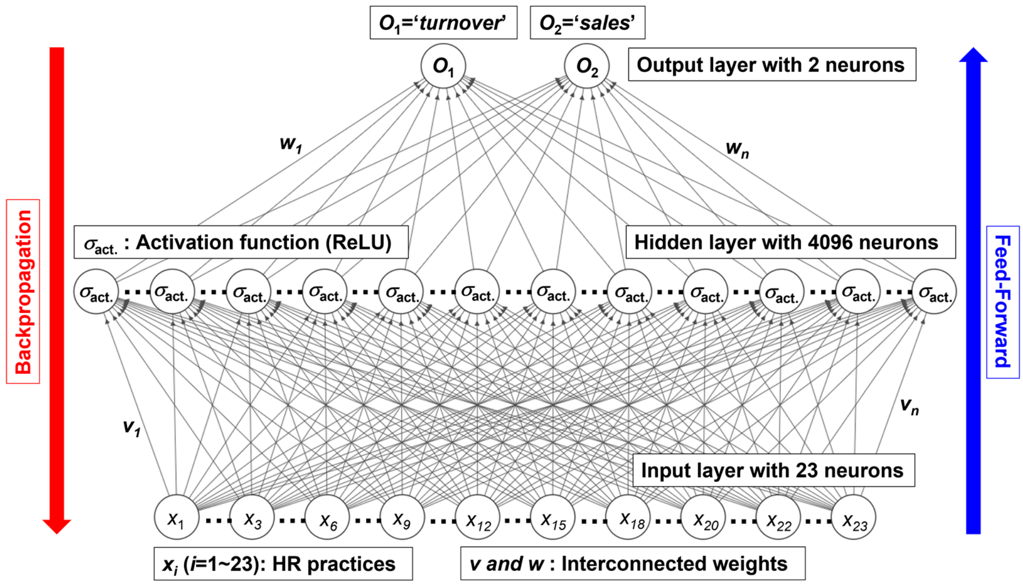


Figure 1. The architecture of a single-layered neural network.

The Rectified Linear Unit (ReLU) activation function is a popular choice for deep neural networks because of its several advantages in backpropagation. It is computationally efficient, avoids the vanishing gradient problem, promotes sparsity, and is easy to optimize. Compared with other activation functions, ReLU involves a simple thresholding operation, and its derivative is always either 0 or 1, which makes it more efficient and stable during backpropagation. ReLU can lead to sparse representations in neural networks, which helps to reduce overfitting and improve generalization performance by eliminating irrelevant features and reducing the dimensionality of the input. In this study, the $\sigma_{\text{act.}}$ was employed by the ReLU function (3), as expressed in Equation (3). This activation function is a positive value if $\sigma_{\text{act.}}$ exceeds 0; otherwise, $\sigma_{\text{act.}}$ is 0.

$$\sigma_{\text{act.}}(y) = \text{ReLU}(y) = \begin{cases} y & (\text{ReLU}(y) \geq 0) \\ 0 & (\text{ReLU}(y) < 0) \end{cases} \tag{3}$$

Training and test datasets comprised 80% and 20% of a total of 1221 data, respectively. Based on these datasets, the interconnected weight, v, and w, between the input, hidden, and output layers were obtained using the stochastic gradient descent optimizer (Keskar and Socher 2017). This optimizer is advantageous as convergence is fast during the training at each step and can reduce the probability of falling in the local optimum by stochastic shooting when updating interconnected weights. Furthermore, regularization is a technique used in BPN models to prevent overfitting and improve the generalization performance of the model. It involves adding a penalty term to the loss function (i.e., MSE, MAE, and R^2) that encourages the weights of the network to be small. There are different types of regularization techniques, such as L1 and L2 regularization, which differ in the way the penalty term is calculated. These techniques can reduce the complexity of the network, prevent the model from memorizing noise in the training data, and improve its ability to generalize to new, unseen data. In this study, the training parameters were established, as represented in Table 2. The L1 regularization (Tsuruoka et al. 2009) was employed with Equation (4). Here, λ is the parameter of L1 regularization, and w is the interconnection weight of the BPN model.

$$\text{Loss} = \frac{1}{n}\sum_{i=1}^{n}\left\{L(O_i, O_{p_i}) + \frac{\lambda}{2}|w|\right\} \tag{4}$$

Table 2. Training parameters for training the BPN model.

Learning Rate (*h*)	Momentum (*g*)	L1 Regularization (*l*)	Epoch	Batch Size
0.0005	0.9	0.001	200	8

4.4. Validation

The accuracy and validity of the BPN model were evaluated using the k-fold cross-validation (Li et al. 2010) method using sequential shuffling with 20 folds according to the randomness of the training and test datasets at a fixed rate (Figure 2). Furthermore, the quantitative metrics of accuracy and validity were assessed using the mean squared error (MSE), mean absolute error (MAE), and R-squared (R^2) value, as expressed in (5)–(7). Here, O_i is the actual training or test data of the i-th input data, O_{pi} is the predicted value from the BPN model of the i-th input data, O_m is the mean value of O_i, SSR is the residual sum of squares, and SST is the total sum of squares.

Figure 2. Schematic of the k-fold cross-validation.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(O_i - O_{p_i})^2 \tag{5}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|O_i - O_{p_i}\right| \tag{6}$$

$$R^2 = 1 - \frac{SSR}{SST} = 1 - \frac{\sum_{i=1}^{n}\left(O_i - O_{p_i}\right)^2}{\sum_{i=1}^{n}\left(O_i - O_m\right)^2} \tag{7}$$

k-fold cross-validation stands as a fundamental technique in the realm of machine learning, serving to evaluate model performance by iteratively partitioning the dataset into k subsets, with each subset utilized as a validation set while the remaining subsets are designated for training. This methodological approach carries significant merit, particularly evident in scenarios characterized by limited dataset sizes, substantial data variability, and intricate model architectures. It enables a more robust estimation of model performance compared to simplistic train–test splits, offering insights into potential overfitting or underfitting phenomena and facilitating the fine-tuning of model parameters. Nonetheless, it is imperative to acknowledge the computational overhead associated with k-fold cross-validation, particularly notable in the context of large datasets or computationally intensive models. Despite this consideration, the method remains a cornerstone in the rigorous evaluation of machine learning models, embodying a widely accepted and academically endorsed practice within the field.

In this study, k-fold cross-validation with 20 folds was conducted to evaluate the accuracy and validity of the BPN model using the aforementioned metrics. These results are summarized in Table 3. The best model was that of the 11th fold among the 20 folds, and the MSE, MAE, and R^2 of the model are 0.4981, 0.2773, and 0.5985, respectively. Furthermore, a good training result is observed in that the validation-loss function is considerably less than the training-loss function (Figure 3). Regarding R^2, the model fitness of the 11th fold is comparatively low (Figure 4). Although the R^2 value can be increased by modifying the BPN architecture, this model was chosen to avoid overfitting the predicted values.

Table 3. Evaluation of the accuracy and validation for the trained BPN model via k-fold cross-validation (The best model is indicated in bold).

k-Fold	MSE	MAE	R^2
0th	0.5320	0.2731	0.5578
1st	0.5173	0.2912	0.5790
2nd	0.5069	0.2783	0.5886
3rd	0.5105	0.2808	0.5885
4th	0.5114	0.2817	0.5865
5th	0.5282	0.2819	0.5754
6th	0.5354	0.2837	0.5686
7th	0.5701	0.2910	0.5269
8th	0.5240	0.2888	0.5748
9th	0.5310	0.2834	0.5662
10th	0.5053	0.2808	0.5918
11th	**0.4981**	**0.2773**	**0.5985**
12th	0.5185	0.2725	0.5688
13th	0.5085	0.2781	0.5909
14th	0.5349	0.2932	0.5486
15th	0.5142	0.2881	0.5856
16th	0.5050	0.2811	0.5926
17th	0.5007	0.2801	0.5948
18th	0.5954	0.2775	0.4552
19th	0.5128	0.2828	0.5857
Mean	0.5225	0.2823	0.5712

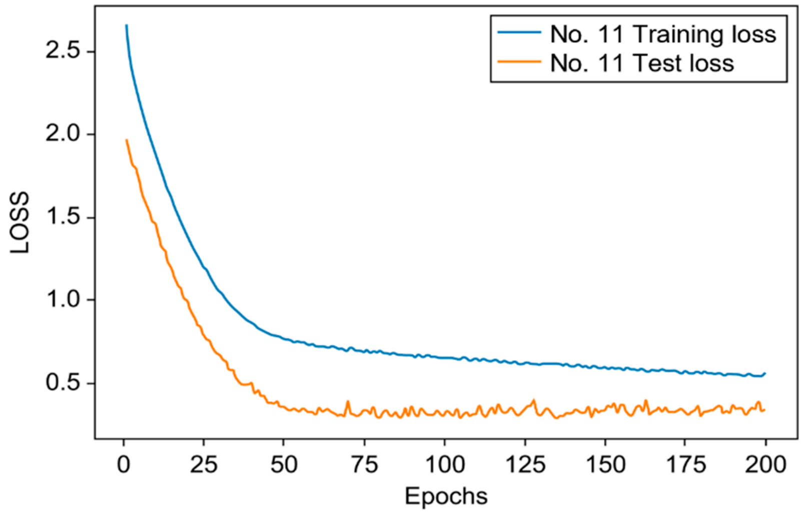


Figure 3. Trends of training- and validation-loss functions for the best model of the 11th fold.

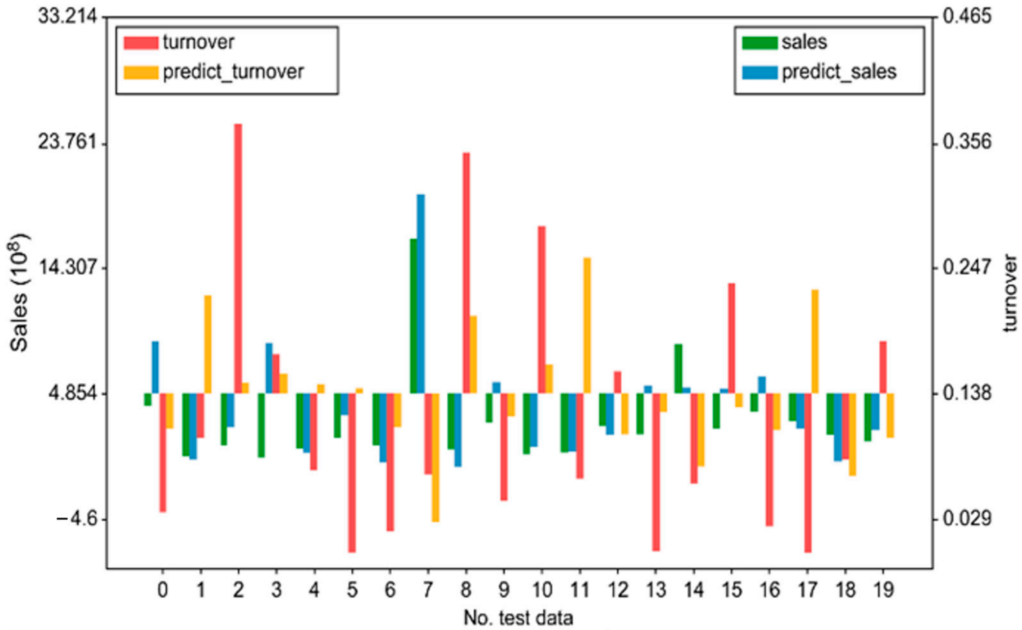


Figure 4. Comparison between the predicted and actual values (employee turnover and firm sales) for the best BPN model of the 11th fold using the validation data.

4.5. Backpropagation Neural Network-Based Causality Analysis

Causality analysis is widely used in social sciences to describe the cause of social phenomena. This study performed a BPN-based causality analysis based on interconnected weight among the input, hidden, and output layers to investigate the relative importance of HR practices and firm performances. The procedures for the BPN-based causality analysis are indicated below (Takeuchi et al. 2009).

(1) The interconnected weights between the input and hidden layers and between the hidden and output layers for the well-trained BPN model comprising a single layer denote v_{ij} and w_{jk}, respectively. The sum of the magnitude of the interconnected weight (S_j) between all input-layer neurons and the j-th hidden layers was computed using (8).

$$S_j = \sum_{i=1}^{N} |v_{ij}| \tag{8}$$

(2) The fraction of signal (f_{ij}) is defined as the degree of the information flow between the i-th input-layer neurons and the j-th hidden layer using the magnitude of the interconnected weight. The f_{ij} was calculated using (9).

$$f_{ij} = \frac{|v_{ij}|}{S_j} \tag{9}$$

(3) η_{ik} is the sum of the fraction of signal for all interconnected weights between the input-layer and hidden-layer neurons, which is multiplied by w_{jk} between the j-th hidden-layer and k-th output-layer neurons. η_{ik} was computed using (10).

$$\eta_{ik} = \sum_{j=1}^{J} \frac{|v_{ij}| \cdot |w_{jk}|}{S_j} \tag{10}$$

(4) H_k is defined as the sum of all η_{ik}, which is the fraction of the signal on all v_{ij} and w_{jk}, which is between the input- and hidden-layer neurons and between the hidden- and output-layer neurons, as represented in (11).

$$H_k = \sum_{i=1}^{N} \eta_{ik} \tag{11}$$

(5) The component, t_{ik}, of the transition matrix that indicates the degree of contribution of the i-th input-layer neuron to the fraction of the k-th output weight was calculated using (12).

$$t_{ik} = \frac{\eta_{ik}}{H_k} \tag{12}$$

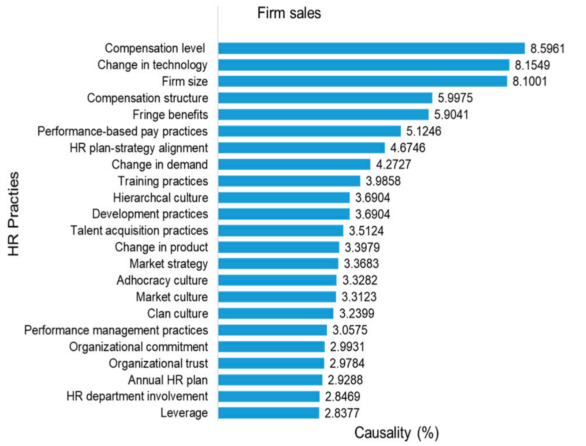
(6) Component t_{jk} was normalized by (13) to easily identify the degree of quantitative contribution of the i-th input-layer neuron to the k-th output-layer neuron. The sum of all $\bar{t}_{ik}$ is always unity.

$$\bar{t}_{ik} = \frac{t_{ik}}{\sum_{i=1}^{N} t_{ik}} \tag{13}$$

In summary, when considering the specific k-th column components of the normalized transition matrix, the effect of each input component on the k-th output component can be quantitatively evaluated. Considering that the sum of all components of the transition matrix in the k-th column is unity, this influence is indicated as a fractional quantity and can identify dominant input variables for output. Furthermore, the BPN-based causality analysis can be conducted for multiple hidden-layer networks by extending the dimension of interconnected weights (Lee 2008).

4.6. Results of Causality Analysis and Parameter Study

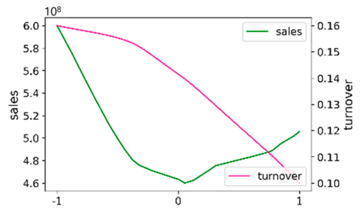
The results of the causality analysis are shown in Figure 5. For firm sales, *compensation level*, *change in technology*, and *firm size* are sequentially significant; HR practices, as expected, had a substantial influence. For firm sales, among 11 variables for HR practices and HR departmental activities used in the prediction, 8 are included in the top 12 important variables. For employee turnover, 7 variables are included in the top 12 important variables. The results are consistent with those of previous studies that showed HR practices and implementation matter (Huselid 1995; Jiang et al. 2012; Combs et al. 2006; Arthur 1994). Although causality analysis unveiled the relative importance of all the independent variables, it did not provide information on their directions of effects. Thus, to investigate the trend of firm sales and employee turnover by changing the value of each HR practice and firm characteristics, a parameter study was conducted using the trained BPN model. Firm sales and employee turnover were computed by increasing the specific HR practice or firm characteristics from −1 to 1 under the value of the remaining 22 variables, which was established at 0. The trend of firm sales and employee turnover according to each HR practice is shown in Figure 6.



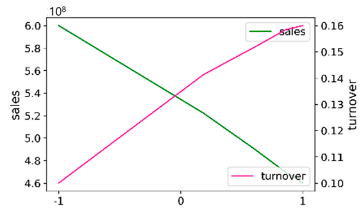
(**a**) Relative importance of explanatory variables on firm sales

(**b**) Relative importance of explanatory variables on employee turnover

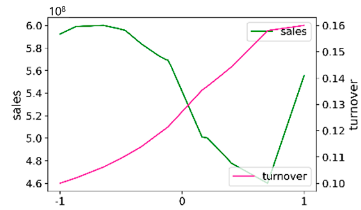
Figure 5. The quantitatively relative importance of explanatory variables on firm sales (**a**) and employee turnover (**b**) via BPN-based causality analysis.



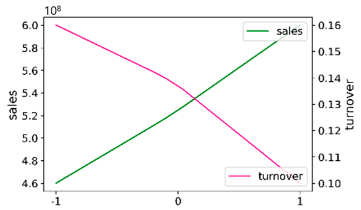
(**a**)



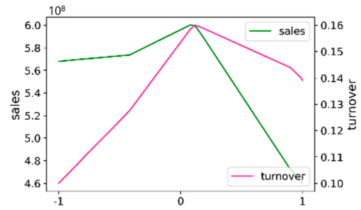
(**b**)



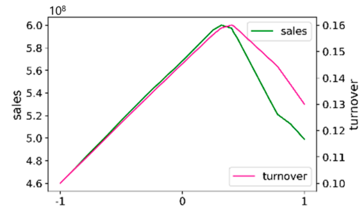
(**c**)



(**d**)



(**e**)



(**f**)

Figure 6. *Cont.*

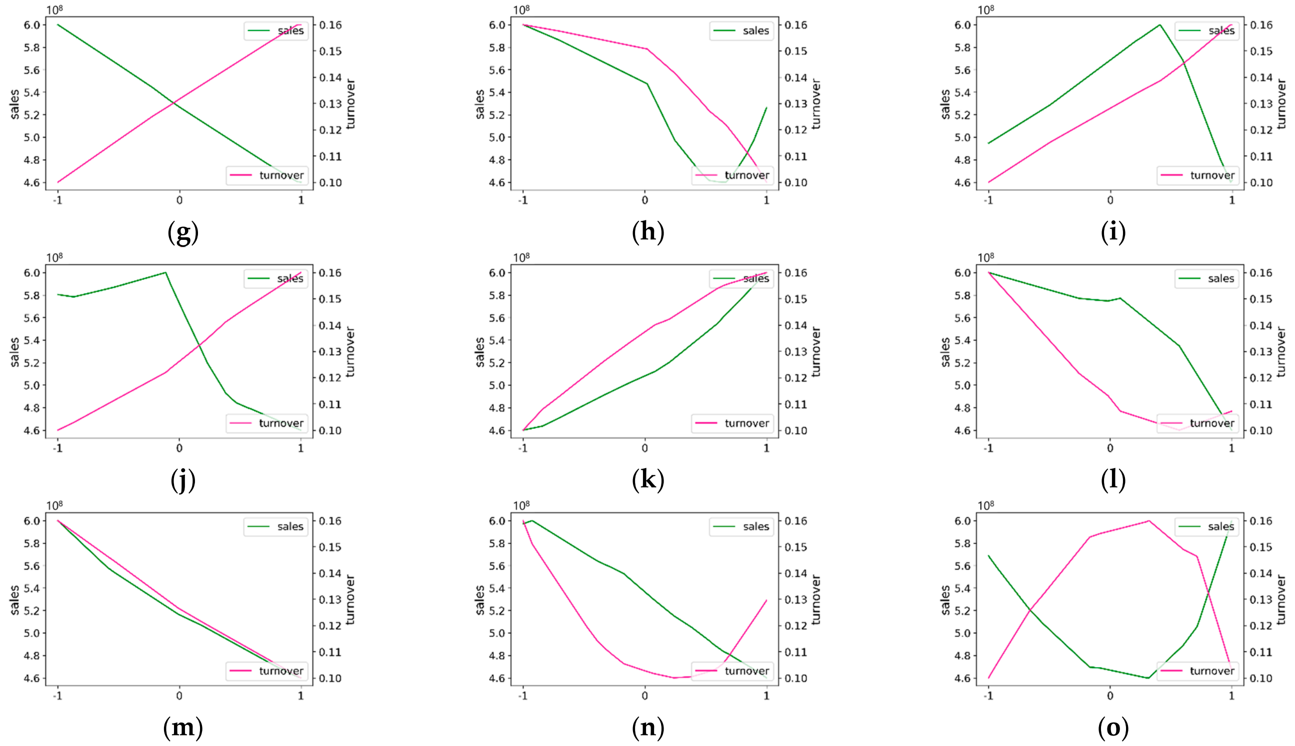


Figure 6. Partial dependence plots of explanatory variables on firm sales and employee turnover: (**a**) Compensation level. (**b**) Compensation structure. (**c**) Performance-based pay practices. (**d**) Fringe benefits. (**e**) Talent acquisition practices. (**f**) Performance management practices. (**g**) Training practices. (**h**) Development practices. (**i**) Annual HR plan. (**j**) HR plan-strategy alignment. (**k**) HR department involvement. (**l**) Organizational trust. (**m**) Organizational commitment. (**n**) Change in demand. (**o**) Change in technology.

5. Results and Discussion

5.1. Main Finding

The results generally support the importance of HR practices in predicting firm sales and employee turnover. Furthermore, as expected, the partial dependence plot in Figure 6 reveals complex relationships between explanatory variables and the two dependent variables. The main findings can be summarized as follows.

First, HR practices related to compensation are most influential in predicting firm sales and employee turnover. For firm sales, *compensation level*, *compensation structure*, *fringe benefits*, and *performance-based pay practice* are the first, fourth, fifth, and sixth most important variables, respectively. For employee turnover, *compensation level*, *performance-based pay practice*, *training practice*, and *compensation structure* are the second, third, fourth, and sixth most important variables. In previous HRM studies, compensation and other benefits, frequently classified as motivation-enhancing HR practices, have been considered to affect employee turnover and firm performance by strengthening employee motivation and human capital (Jiang et al. 2012). A previous study also observed the importance of compensation on performance measured by firm sales based on ML techniques using the HCCP dataset (Choi et al. 2021). However, according to the present study, the relationships between compensation practices and the two outcomes are more complex than previously suggested.

Specifically, Figure 6a–c show that the compensation level and number of performance-based pay practices have nonlinear relationships with firm sales, but compensation structure has a relatively clear negative relationship with firm sales. Additionally, although the employee turnover rate decreases with the compensation level, it increases with the compensation structure and the number of performance-based pay practices. In addition, as shown in Figure 6d, fringe benefits, which can be viewed as a form of compensation, have desirable effects on the two outcomes. Fringe benefits decrease employee turnover and enhance firm performance. In summary, HR practices related to compensation are important factors in predicting firm sales and employee turnover. However, employees in Korean firms tend to react positively to the rise in total compensation but react negatively to an increase in the proportion of performance-based pay and the number of performance-based pay practices. Fringe benefits can also easily be used to promote behaviors that can improve firm performance and reduce turnover.

Second, the effects of *talent acquisition practice* and *performance management practice* are relatively weak, as shown in Figure 5a,b. *Talent acquisition practice* is the 12th and 19th important variable in predicting firm sales and employee turnover, respectively. Similarly, *performance management practice* is the 18th most important variable for firm sales and employee turnover. The limited effects might be because those practices are already institutionalized (Meyer and Rowan 1977; Boon et al. 2009; Gooderham et al. 1999). In other words, several Korean firms rely on the external labor market to acquire key talent and use diverse performance management practices. Thus, the difference in the two outcomes explained by those practices is relatively limited. Regarding the direction of effects (Figure 6e), *talent acquisition practice* exhibits an inverted-U shape relationship with the two outcomes of the study. Figure 6f shows these relationships. These results suggested that despite their institutionalized nature, talent acquisition and performance management practices can still be effective management tools to an extent. However, HR managers should determine the appropriate intensity of such practices. For example, the excessive utilization of external labor market and performance management practices may cause competitive interactions inside organizations, leading to unintended negative effects on organizational effectiveness. Given that the detailed causality may be more complex, the observed relationship should be investigated in future studies.

Third, compared with other HR practices, the effects of training and development on the two outcomes are modest. *Training practice* and *development practice* are the 9th and 10th most important variables in predicting firm sales, respectively. They are also the 4th and 13th important variables in predicting employee turnover. Previous studies have suggested that training and development increase firm performance and decrease turnover intention (Arthur 1994; Shuck et al. 2014). However, our results showed that the effects are more complex than previously suggested. Figure 6g–h show that training affects sales negatively, and the effect of development practice changes from negative to positive as the level increases. These complex relationships can be further explored by considering the training and development content and the characteristics of strategy and operation. Considering the aforementioned content, a plausible explanation of the effects of training and development practices on employee turnover can be developed.

Specifically, training enhances employee turnover, but development reduces employee turnover. This contrasting effect might be caused by the difference in the characteristics of the two practices. Development practices, such as career development programs, mentoring, learning groups, and job rotation, are internally implemented to enable employees to accumulate firm-specific knowledge. Contrarily, training programs, which are frequently outsourced to specialized external institutions, provide employees with general skills and the latest knowledge. Thus, although enhanced firm-specific skills can reduce employee turnover, strengthened employability will lead to employee turnover (Nelissen et al. 2017; Benson 2006; De Cuyper et al. 2011). Future studies need to explore this topic by focusing on the fit between the characteristics of two types of practices and firm strategy and operation.

Fourth, regarding HR departmental activities, this study evaluated the relative importance and direction of the effects of *HR plan-strategy alignment*, *annual HR plan*, and *HR departmental involvement*. They are the 7th, 21st, and 22nd most important variables for sales (Figure 5a). They are also the 10th, 15th, and 20th most important variables for employee turnover (Figure 5b). Thus, their effects are relatively small and weak. In addition, as shown in Figure 6i–k, the directions of effects are not clearly evident, and there are negative effects that require further investigation. However, the results should be interpreted with caution because the measurement focused on the existence or degree of the practices, not their actual contents. Thus, future studies on these topics could start by understanding the goals of practices that can determine the direction of the effects.

Fifth, although the study focused on HR practices, there were interesting findings on the effects of employee attitude and changes in demand and technology. Many studies have reported the positive effects of organizational trust and commitment on employee retention and job performance (Mathieu and Zajac 1990; Meyer et al. 2002; Colquitt et al. 2007; Dirks and Ferrin 2001). According to our findings, *organizational trust* and *commitment* have a relatively minor effect on the two outcomes (Figure 5a,b). In particular, their effects on sales are minimal, and those on employee turnover are considerably less than those on compensation practices. Thus, our findings suggested that compared with other factors, *organizational trust* and *commitment* may not be influential factors in Korean firms. However, they have the expected effects on employee turnover (Figure 6j–k). Noteworthily, *change in technology* is the second and fifth most important variable in predicting firm sales and employee turnover, respectively (Figure 5a,b). *Change in demand* is also the eighth and most important variable in predicting firm sales and employee turnover, respectively. Changes in the market (demand for the primary product) and inside the organization (technology used in the organization) also have nonlinear relationships with the two outcomes (Figure 6n,o). Although such relationships cannot be easily explained, the fact that there were inflection points, particularly regarding employee turnover, can provide HR managers with guidance on when HR practices should be revised.

5.2. Implications

The theoretical implications of this study are as follows. First, this study contributes to the existing literature on HRM systems and firm performance by examining the relationship between a large number of individual HR practices and firm performance. Previous studies have typically focused on a limited number of individual HR practices or on bundles of HR practices. This study's findings suggest that a wider range of HR practices may be important for firm performance. Second, this study addresses the issue of endogeneity problem by using a variety of methods to control for potential confounding factors. This helps to ensure that the results of the study are not due to other factors, such as firm size or industry. Third, this study provides new insights into the mechanisms by which HR practices influence firm performance. The findings suggest that HR practices can influence firm performance through a variety of channels, including organizational culture and employee work attitudes, employee turnover, and strategy.

This study presents the following managerial implications. First, HR managers can use the results of this study to understand which HR practices they should pay attention to. In formulating and implementing HR practices, HR managers are asked to enhance firm sales and reduce or, at least, maintain employee turnover. Although previous studies have provided ample evidence that a bundle of HR practices enables HR managers to achieve the two outcomes of the present study, these studies have rarely focused on the relative importance of each HR practice on the two goals. Focusing on widely used HR practices and other individual and organizational characteristics, this study provides information on the relative importance of HR practices on firm sales and employee turnover. The results are valuable guidelines for HR managers to effectively allocate limited resources to different types of HR practices.

Second, our study stressed that HR managers should exercise caution when introducing new compensation practices. Faced with a talent shortage, many Korean firms have increased pay levels and the proportion of performance-based pay to attract talent from the labor market. Such practices are also used to align existing employee motivation and behaviors with the overall goals of the firms. This trend is frequently accompanied by the introduction of various compensation management practices. However, as revealed in the analysis, although compensation level was negatively associated with employee turnover, the proportion of performance-based pay and the number of performance-based pay practices were positively associated with employee turnover. This result implied that current compensation practices aimed at attracting and motivating talent should be reconsidered. Specifically, given that performance-based pay is a widely used compensation practice, our analysis suggests that firms seeking to reinforce performance-based pay should keep their compensation practices straightforward by reducing the number of performance-based pay practices.

Third, this study provides insights into when existing HR practices should be revised. From the perspective of SHRM, HR practices should be revised when firms change their strategies to reflect changes in the external environment, such as changes in demand, and that determine internal conditions, such as technology. According to this study, changes in technology and demand for primary products are influential in predicting sales and employee turnover. Given that such changes are inevitable for a firm to maintain a competitive advantage, HR managers in firms facing such changes should pay attention to their HR practices. Notably, according to Figure 6n–o, the inflection points exceeded zero, indicating that managers should reevaluate existing HR practices when the changes exceed the level taken by competitors. Thus, this study provides more detailed guidelines than general theoretical suggestions on when HR managers should consider revising current HR practices.

Fourth, this study observed many complex relationships between HR practices and the two outcomes, which are challenging to explain theoretically. Notably, the relationships between certain predictors and the two outcomes were nonlinear and cannot be easily explained. These results would have been determined by the ML algorithm aimed at improving explanatory power. However, the complex nature of the relationships suggests that SHRM scholars should utilize a pattern discovery approach as well as a traditional theory-driven approach to provide practitioners with more practice guidance. Thus, the content of the practices and the context under which such practices are implemented should be carefully considered in future studies.

5.3. Limitations

This study has certain limitations that future studies can address. First, it did not consider the effects of each firm's distinctive HR practices. Our analysis is based on secondary data (HCCP); thus, this study did not consider HR practices that are not included in the survey. However, given that idiosyncratic conditions of firms can cause a difference in HR practices between firms, future studies should investigate the effects of customized HR practices that reflect each firm's specific goals or purpose. Second, the study's sample of firms was limited to the manufacturing industry. Thus, the results may not apply to other industries, such as the service industry. Future studies may emphasize the difference in the effects of the same HR practices across industries. Third, the analysis did not investigate the nonlinear interactions between the effects of the two explanatory variables on the outcomes. This study aimed to examine the effects of HR practices on firm sales and employee turnover, emphasizing the direct effects of each HR practice. However, the effects of each HR practice can be further enhanced or reduced depending on other HR practices and individual and organizational characteristics (Han et al. 2019; Becker and Gerhart 1996). Future studies can explore nonlinear interdependences based on this theoretical argument. This approach will be another way to reexamine the complex nonlinear effects of HR practices that this study observed. Lastly, this study utilizes the empirical Bayes (EB) estimation method with the expectation–maximization (EM) algorithm to address the characteristics of the panel data, which is an incomplete dataset with missing values. The EM algorithm-based EB estimation method repeatedly estimates the parameters from the given incomplete data and estimates the complete data sufficient statistics. It then utilizes these statistics to estimate the maximum likelihood value. This method does not replace missing cases or values. Instead, it estimates the parameters by estimating the complete data. Therefore, it can overcome the limitations of missing variables or cases in the data (Raudenbush and Bryk 2002).

In terms of explanatory capacity, the limitation emerges within machine learning models grounded in data-driven approaches, as they lack the capability to explicate the relationship between input and output variables, owing to their exclusive reliance on data. Numerous researchers have endeavored to mitigate this limitation by explaining the relationship between input and output variables in a rational manner. Furthermore, they have introduced the concept of explainable and interpretable artificial intelligence models to address this challenge, with the objective of fostering a meaningful comprehension of the association between input and output variables. Consequently, the significance of a machine learning model lies in its capacity to unveil an intelligible and reasoned interpretation of this association.

6. Conclusions

Effective HR practices contribute to firms by supporting strategy implementation. This supporting role can be achieved when the HR practices are aligned with strategic goals and can acquire, develop, motivate, and retain capable employees. For example, one of the main research results seems to be attributed to the following wage system in the Korean labor market. For a long time, Korean companies have operated a wage system based on seniority. The seniority system has the advantage of making it easy to secure and retain skilled workers and flexibly assign them to necessary tasks. Therefore, it was a system that could compensate for the labor shortage in the Korean labor market due to rapid industrialization since the 1970s. After experiencing the foreign exchange crisis and the subprime mortgage crisis in the 2000s, many Korean companies introduced a performance-based compensation system. However, the performance-based compensation system is unfamiliar to Korean workers who are accustomed to the old seniority-based organizational culture. Therefore, many companies need to pay attention to the fairness of the performance-based system and communication about the performance system to reduce resistance from workers when introducing the performance-based compensation system.

In this study, the relative importance and the direction of the effects of widely used HR practices in Korean manufacturing firms were examined. The study identified influential HR practices that predict firm sales and employee turnover and provided evidence of complex relationships between HR practices and the two outcomes. The results emphasized that HR managers do not need to pay equal attention to all HR practices and should review existing HR practices depending on relative changes to competitors' internal or external conditions. This study provides practitioners with practical guidelines and encourages scholarly works that reexamine the complex effects of HR practice on organizational effectiveness.

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