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Research Article

Exploring the Nexus Between Socially Responsible Human Resource Management, Employee Green Behavior, Learning Goal Orientation, and Moral Identity: A Novel Perspective Using BSP-CRF Technique

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Abstract *– This proposed aimed to understand how green human resource management (GHRM) enhances workers' environmental performance. It focuses on how GHRM practices affect employees' voluntary and task-related green performance behaviors. Gender and individual personal environmental values function as moderators, and organizational identity acts as a mediator. The method primarily entails three stages: preprocessing, feature selection, and model training. Missing data handling and min-max normalization are part of the preprocessing, with min max yielding the best outcome. There are two main categories of agents in feature selection: information selection agents and appreciation providing agents. For the purpose of evaluating pupils' progress, this system builds a BSP-CRF model. This approach seems dated when compared to BSP and CRF. The data clearly shows an improvement, with an incredible accuracy percentage of 96.34%.*

Keywords— *Green Human Resource Management (GHRM), Boltzmann Sparse Probabilities (BSP), Employee Green Behaviour*

Introduction

Many companies have begun to use green management practices after becoming interested in the global literature on the topic. This interest has primarily come from the service and manufacturing sectors. Companies care about environmental problems and are trying to solve them. Environmental injustice, climate change adaptation, and depleting renewable energy resources are just a few of the ecological difficulties that organizations around the world are confronting. Concern about climate change and environmental degradation has been voiced by governments, corporations, and the public alike. Unexpected and unexpected resource consumption in pursuit of economic expansion, is the root cause of ecological problems. The success or failure of an organization's environmental protection initiatives is heavily dependent on the activities of its employees. Businesses worldwide are promoting environmental initiatives and implementing green programs inside their own workforces. The goal of human resource strategy should be to attract, retain, and develop talented individuals. Therefore, a human resources plan makes it easier to be competent and competitive when applying for jobs. Human resources play a pivotal role in determining a company's fortunes. An approach for companies to invest in their employees' professional development is to provide a forum where the system may voice their opinions and ideas. Employees, in the simplest terms, are what drive a company forward. Human resource management (HRM) scholars have just lately begun to explore Companies have started opening again as a means of bouncing back from the economic shock that the pandemic caused, even though the exact end date of the epidemic is unknown. Nonetheless, the system are navigating these waters with innovative strategies and peculiar rules, like instituting physical separation in the workplace. Managers and HRM professionals have thus encountered a novel and challenging setting due to the pandemic. They need to be resourceful if the system wants to keep their business afloat and help their staff deal with this unusual crisis. Nevertheless, managers and HRM practitioners need current information to help them navigate this crisis, assist their employees, and keep their company afloat. Most companies lack the necessary preparation to deal with crises when they occur. Since this could be an epidemic, it is crucial for scientists to support organizations by providing them with relevant information.

RELATED WORKS

The proposed approach intends to achieve this by gathering relevant literature on eco-friendly practices in the workplace. By using the latest Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) 2020 checklist, the proposed approach may guarantee that our report truthfully portrays the review's rationale, methodology, and findings [1]. This integrated review strategy allowed us to select the most pertinent publications to answer research question while minimizing the possibility of omission or mistake, drawing on prior work [2]. The first to suggest the idea of pro-environmental conduct, hence the proposed approach only included publications published. The second step was to track down the original data sets. [3] In order to ensure coverage, the proposed approach performed an extensive search in multiple databases, such as EBSCO, Web of Science, Wiley, ProQuest, PsycINFO, and Google Scholar. Lastly, we searched for green behaviours using the following terms: 'citizenship,' 'employee,' corporate, 'firm,' enterprise, business, and 'organ the organizational contextization'; [4]for green practices, the proposed approach used the following terms: 'environmental,' 'proenvironmental,' ecological, 'environmental-friendly,' "green," sustainable, and environmental-friendly."[5] This collection of essays presents strong arguments in favor of taking immediate action to mitigate climate change. But what role can groups play in the fight against climate change? Most studies on climate change have focused on public organizations, although organizations can be either public or private. A probable reason for this could be that a lot of individuals blame corporations for global warming and consider economic growth and consumption as unalterable causes of the problem [6]. The consensus among businesses is as follows: There was a near-universal agreement among a thousand CEOs of one billion companies that fostering environmental sustainability is critical to their companies' long-term success [7]. Strategic initiatives rely on the combined efforts and cumulative behaviors of employees, although an organization's institutional setting influences its environmental impact. Employee green behavior (EGB) refers to "scalable actions and behaviors that employees engage in or bring about that are linked with, and contribute to, environmental sustainability." This psychological analysis thus zeroes in on the nuts and bolts of how a company acts in relation to its surroundings [8]. At home and in the office, there is a correlation between EGB and eco-friendly values and habits. Advocating for a strong pollution prevention program is an example of positive EGB that people who are outgoing and receptive to new experiences are likely to do, whereas endorsing improper handling of hazardous waste is an example of negative EGB that people who place a high value on economics are more likely to do [9]. Individuals can enhance their EGB regardless of whether they have a target related to the environment or not. This is because EGB becomes relevant to an existing personally significant purpose when self-concordance is improved. [10] define employee green behavior as "employee' engagement in green behaviors, including employees' actions to perform work in an environmentally friendly way (e.g., recycling, rational use of resources, and participation in environmental initiatives, setting of more green policies)". According to[11], "green behavior" refers to employees' "scalable actions and behaviors that are linked with and contribute to or detract from environmental sustainability". Workers can help the environment by doing things like turning off lights when the system leave the office to save energy, using electronic editing tools instead of printing documents to avoid paper mistakes, teleconferencing instead of travelling to meetings to save resources, and recycling [12]. Some of the main factors that motivate employees to act environmentally responsibly include green organizational climates, attitudes and beliefs, organizational sustainability policies, corporate environmental strategy, demographics, green HRM practices, environmental knowledge, corporate social responsibility, and organizational sustainability policies [13]Certainly, more investigation into the effects of corporate social responsibility (CSR) on eco-conscious behaviors among hotel industry workers is required. So, as a social consequence of CSR, the proposed approach examines the link between happy hotel employees and eco-friendly practices. [14] proposed the social information processing theory, which states that people's social environments influence their beliefs and behaviors. Social information processing theory postulates that employees' views about their workplace influence their behavior and outlook on life. Authentic CSR initiatives should motivate workers to do their part for the planet [15]. In recent decades, environmental impacts have garnered considerable interest from various quarters, including scholars, policymakers, and advocacy organizations [16]. Environmental activities, pressures from organizations, and legislative efforts have all contributed to a recent uptick in sustainability awareness and competence in environmental problem solving [17]. There are various areas of businesses that have adopted green practices, such as green leadership and green product/process methods. Attention this research, the proposed approach zero attention on green transformational leadership (GTFL) [18] and its effects on environmentally conscious actions taken by employees and the success of businesses in this area. The reason behind this is that transformational leaders prioritize environment management as part of their efforts to change the behavior of their firms and people.[19] This editorial from HRMJ draws on a variety of viewpoints on how HRM research may evolve in light of recent advances in generative AI and the new problems it is posing for HRM and for the way businesses operate more broadly. [20] Primary objective is to provide a summary of recent advancements in the field of human resource management. Secondary objective is to compile a list of potential research avenues that HRM scholars can take to advance our understanding of generative AI by advancing theory and evidence. The proposed approach wanted a bird's-eye view of the ever-changing terrain, so the proposed approach polled famous academics for their thoughts on core HRM issues. [21] The perspectives highlight the need of HR professionals staying abreast of the constantly changing AI landscape, particularly the groundbreaking and transformative potential of generative AI on HRM tactics, processes, and results.

METHODLOGY

Company rules, practices, and procedures impact employee understanding and engagement, which in turn impacts the implementation of behavioral objectives. Through the use of a daily diary study investigated the relationship between corporations' environmental policies and pro-environmental, or "green," attitudes. Additionally, it sought to determine if green psychological climate influences the relationship between employees' daily aspirations for green action and their actual environmental behaviour the following day.

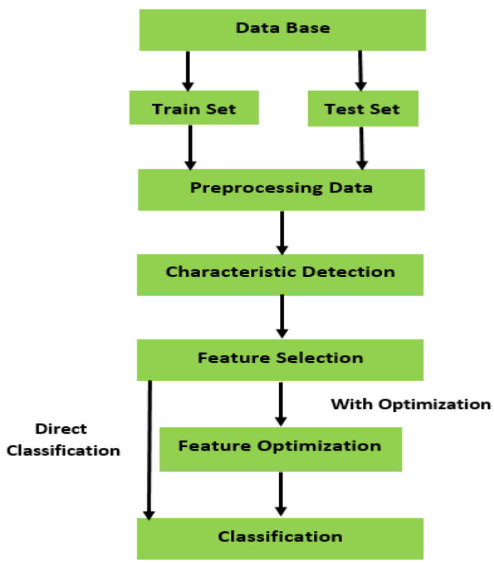

Fig 1. Levels of the Recognition System

First, the data is extracted from a standard database; second, it is pre-processed; third, features are selected; fourth, the features are optimized; and last, the results are classified. This is the five-step process that constitutes a biometric recognition system, as shown in Figure 1. of all the processes involved in a biometric system, feature extraction and optimization have the most impact on overall performance.

A. *Data Preprocessing:*

Due to its importance in enhancing data quality, data processing is a prerequisite for data analysis. Definition of Data Processing According to One Source, Data Processing is "the collecting and manipulation of data pieces to produce meaningful information." To find out how eco-conscious the staff were, this phase used the most important data points from the dataset. The following stage involved categorizing the eco-friendly actions taken by the staff.

1. *Handling Missing Data Using RF Method:*

One common method for attributing missing data is to use random forests (RF)-based techniques. The missing value plot of the training dataset is shown. It has the skills required to manage different kinds of missing data, balance large data sets, and remain adaptable in the face of interactions and nonlinearity [22]. Data on the effectiveness of the various RF imputation methods that are currently available are few. Using a wide variety of distinct missing data methodologies and a wide range of heterogeneous data sets, the imputation performance of several RF methods was evaluated. Proximity imputation, on-the-fly imputation, and imputation based on multivariate unsupervised and supervised splitting are some of the techniques used; the latter is an extension of a noteworthy novel imputation technique known as miss Forest.

2. *Min-Max Normalization:*

Utilizing Equation 1 and the min-max normalization method, the characteristic is scaled inside the [0,1] range. One common method for attributing missing data is by using random forests (RF) based techniques. Here is a visual representation of the training dataset's missing values. Adapting to interactions and nonlinearity is a breeze, and it can manage enormous data sets and missing data types of all kinds. [23] The relative efficacy of the various RF imputation methods is still unknown. The proposed approach used a wide variety of heterogeneous data sets and several missing data procedures to examine the imputation performance of various RF approaches. Proximity imputation, on-the-fly imputation, and imputation based on multivariate unsupervised and supervised splitting are some of the methods used in this field. The latter is an outgrowth of a significant original process called miss Forest.

$$q' = \frac{q - min_E}{max_E - min_E} \tag{1}$$

Here, min_E _E and max_E _E-stand for the lowest and highest values of characteristic E, correspondingly. Both the original value (q) and the normalized value q^' are represented in attribute E. According to the previous equation, the minimum and maximum feature values are mapped to 1 and 0, respectively.

B. *Feature Selection:*

1. *ISA:*

In order to find connections between characteristics or employee information, F-score correlations are examined. Methods for selecting features include it. Feature selection is a common optimization technique for reducing data dimensionality in many domains, such as pattern recognition, machine learning, data mining, and others. The main objective is to get rid of unnecessary and irrelevant features. While these traits don't supply data mining systems much in the way of predictive information, the system do affect the efficiency and cost-effectiveness of team-based categorization methods. The removal of features is not a simple procedure because it is not always possible to determine if the system are relevant or irrelevant to the target class [24]. The relevance of a feature is defined by its evaluation criteria with respect to other features or to a big collection of features. In datasets with more than two classes of real values, the F-Score is a method for measuring discrimination.

$$= \frac{\sum_{h=1}^{m}\left(\bar{b}_f^{(h)} - \bar{b}_f\right)^2}{\sum_{h=1}^{m}\frac{1}{o_{h-1}}\left(b_{g,f}^{(h)} - \bar{b}_f^{(h)}\right)} \quad (2)$$

Where $b -_f$the mean of the f th characteristic across the entire dataset. Calculates b¯_f^((h)) the mean of the f -th feature in the h dataset. In b_(g,f)^((h)) the h dataset, f is the feature of the g instance. In (2), the discrimination between all classes in the dataset is represented by the numerator, while the discrimination within each class is represented by the denominator. A lack of relationship between two features is shown by a large disparity in their F-score values. A lesser F-Score increases the likelihood that it will be relevant and yield beyer results. Running this algorithm will cause the Information Selection Agent (ISA) to return the data needed by the Attrition Detection Agent (ADA) to determine employee turnover.

2. ADA:

The Attrition Detection Agent (ADA) predicts when employees will leave by using an LSTM Classifier. The LSTM is a type of RNN, or recurrent neural network. It is a method for deep learning that employs many neural network modules. An LSTRN is composed of memory cells, I/O units, and forget units. Each of the four units the memory, processing, input control, and output control is responsible for storing data values for predetermined intervals of time. When it comes to classification and regression, the LSTM deep network is the way to go.

3. Model Training:

i. *CRF*:

Several tasks, including as named entity recognition and part-of-speech tagging, are labelled using CRF as a probabilistic model in deep learning and NLP. A student's performance on a deep learning test can be predicted by CRF using their previous grades as a foundation. In order to simulate the joint probability distribution over a collection of labels, the CRF model takes a set of observations and uses them as an example of a Markov Random Field. In this setting, the student's grades may stand in for the observations, and the labels, their performance on a specific test. Using the observations, the model aims to predict the most likely label sequence. First, a set of features to be used for sequence label forecasting must be defined in order to mathematically derive CRF. Every feature has its own unique pair of labels and observations. The CRF model gets the label conditional probability distribution from the characteristics and observations. Equation (3) demonstrates that the probability distribution is

$$t(d|b,s) = (1/C(b,s))exp\left(\sum_f \left(s_f * i_f\left(d_f, d_f - 1, t\right)\right)\right) \quad (3)$$

Where d is the series of labels, b is the sequence of observations, s is the feature weight vector, and i_f is the feature function that takes a set of labels and an observation and returns a feature score in real value. Any possible label sequence can have its probability distribution normalized using the C(b,s)partition function. Finding the values of s for the weights that optimize the training data's conditional log-likelihood is the goal. This can be achieved using a variety of optimization techniques, including gradient descent. The log-likelihood function of the CRF, as demonstrated in (4)

$$M(s) = \sum_f logt\left(d^f \middle| b^f, s\right) - \mu/2\,\|s\|^2 \quad (4)$$

These things are described by the provided sentence: The regularization parameter , the feature weights vector s, the ith sequence of observations b in the training data, the ith sequence of labels d in the training data, the conditional probability t(d^f│b^f,s)for the sequence label d given the observation sequence b, and the weighted features s are all components of the aforementioned process.

ii. BBM:

Integrating BBMs with CRFs for student data assessment entails two main procedures: pretraining the BBM algorithm and fine-tuning the CRF using the learned representations as input features.

a) Pre-Training the BBM:

For the input data B and hidden variables J in equation (5), the BBM models provided the following explanation of their distribution probabilities.

$$T(B,J) = 1/C * \exp\big(-A(B,J)\big) \qquad (5)$$

This is the definition of the energy function A(B, J) in equation (6).

$$A(B,J) = -sum\big(S_{fh}B_f J_h\big) - sum\big(e_f B_f\big) - sum(x_h J_h)$$

Within the 6th equation, the weight matrix is symbolized as S, the bias vectors as ' e ' and ' x' and the partition function as C. As an example of an unsupervised learning algorithm, the BBM is trained using Contrastive Divergence (CD) and Persistent Contrastive Divergence (PCD). The goal of the learning process, as shown in Equation (7), is to optimize the input data's log-likelihood under the model.

$$\begin{aligned} &logT(B) \\ &= \log sum_{JT(B,J)} \\ &= \log sum_{Jexp(-A(B,J))} - logC \\ &= -I(B) \qquad (7) \end{aligned}$$

The free energy of the input data, F(X), is defined by Equation (8).

$$I(B) = -\log sum_{J(-A(B,J))} \qquad (8)$$

Fine Tuning the CRF:

As demonstrated in equation (9), the CRF models the conditional probability distribution of each set of input variables B

$$T(D|B) = 1/C * exp\big(-A(B,D)\big) \qquad (9)$$

A (B, D), the energy function, is defined by equation (10)

$$A(B,D) = -sum\big(s_{fh}(B,D)\big) - sum\big(x_{f,d}\big) \qquad (10)$$

where S represents the weight vector, x stands for the bias vector, i_g denotes the feature function, and d_f is the i-th component of the output variable D.

By combining the sparse probabilistic model with the Bernoulli Boltzmann and the CRF, a model is produced that can effectively capture the crucial aspects of the student performance data while also accounting for the relationships between the labels. This manner, the proposed approach can improve the accuracy and efficiency of grading students' work. The objective of student performance analysis is to identify the most important characteristics that forecast student outcomes [25]. Finding actionable features in data that is both noisy and highly dimensional could be difficult. It is also important to model the interdependencies between the qualities because they could be dependent on each other. One approach to overcome issues is to combine the Bernoulli Boltzmann and CRF models with a sparse probabilistic model. Sparsity limits are used by the sparse model to separate important features and reduce data noise.

iii. BSP-CRF:

Sparse feature selection is one approach to feature selection for student outcome prediction. The sparse feature selection strategy improves the efficiency and accuracy of the Bernoulli Boltzmann and CRF models when applied to them. To promote modest model weights, the sparse feature selection technique adds a penalty term to the aim function. As a consequence, the model eliminates superfluous characteristics, therefore reducing the data's dimensionality. The understanding that not all data features substantially impact the accuracy of student outcome predictions is a fundamental principle of sparse feature selection. By focusing on the most important features, the proposed approach may improve the model's accuracy and reduce data noise. In especially for real-world applications, lowering the dimensionality of the data directly leads to faster training and prediction times. Sparse feature selection is an effective strategy for high-dimensional data, when the number of features is greater than the size of the sample.

RESULT AND DISCUSSION

There has been a recent uptick in discussions about "green" or eco-friendly practices in the workplace. Research on the factors that influence employees' pro-environmental actions has shown that a positive work atmosphere can boost green practices by releasing pent-up psychological energy. However, most of the results come from research that only examined one time point, and there is a dearth of information about these correlations in the literature overall (i.e., cross-sectional designs). These methods fall short of fully capturing the within-person and between-person heterogeneity in job characteristics that contribute to forecasting employees' environmentally conscious behaviour.

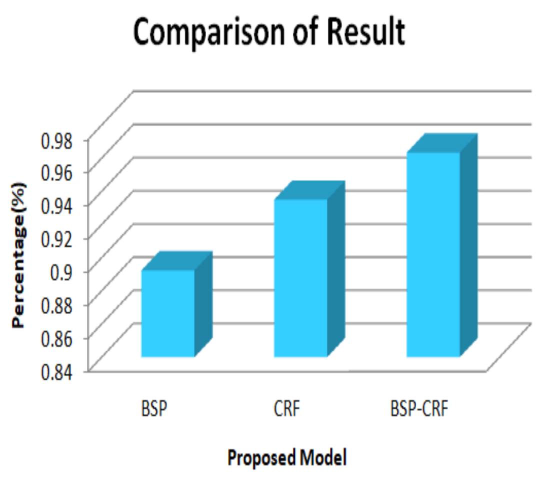

Fig. 2 Comparison of Prediction Results

The three models that are suggested are BSP, CRF, and BSP-CRF. Figure 2 displays the results of the prediction comparison

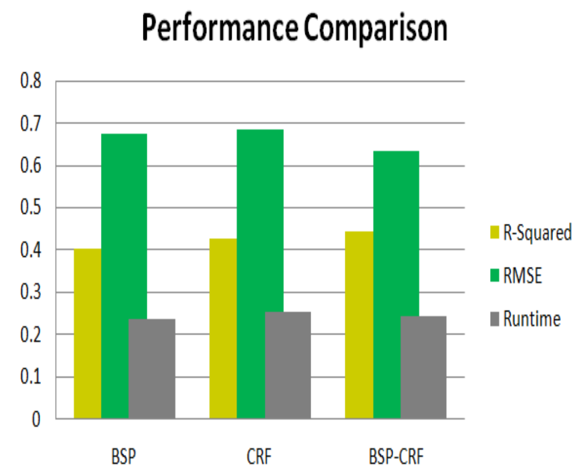

Fig 3. The Proposed Model's Performance Comparison Graph

Graph 3 shows the proposed model's performance comparison. Comparisons of R-squared, RMSE, and runtime are displayed above. It evaluated the suggested model to two others, and it came out on top.

TABLE I. PERFORMANCE MODEL (%)

METHOD	R^2	RMSE	Runtime
BSP	0.405	0.673	0.232
CRF	0.426	0.684	0.284
BSP-CRF	0.445	0.635	0.254

According to Table I, the first group, which includes BSP, CRF, and BSP-CRF, had a duration cut to 0.245 minutes. It was obviously functioning well, though, with an RMSE of 0.635 × 〖10〗 ^4 and an R-squared value of 0.445.

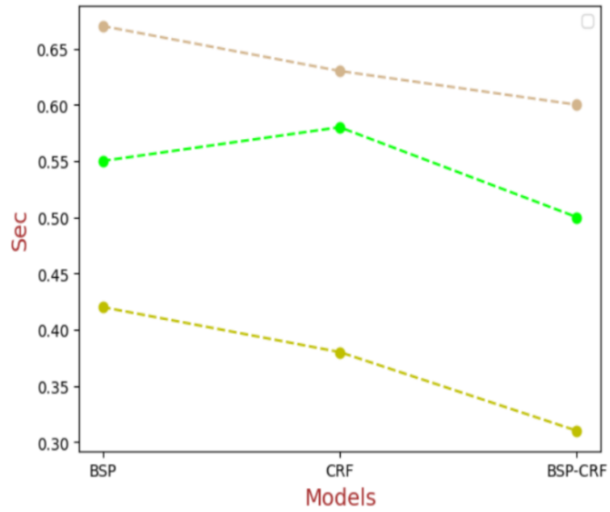

Fig 4. The Suggested Methods Classification Time

Figure 4 shows how the introduced framework's efficiency was affected by the features' selection. Figure 3 show that BSP-CRF had the best Execution Time (ET) at 0.31 seconds.

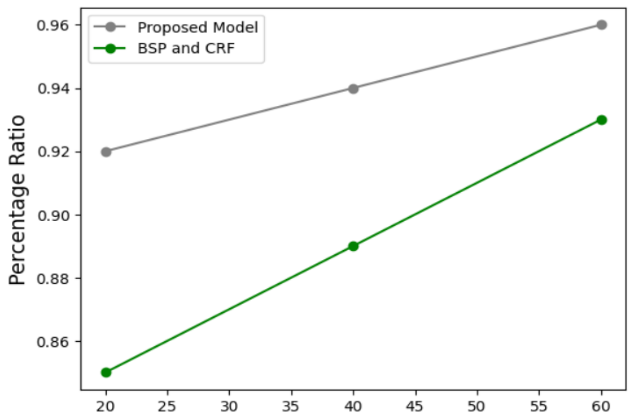

Fig 5. Accuracy Comparison of Model

Figure 5 displays the results of the study's experiments plotted against the suggested method.

CONCLUSION

Many companies today consider environmental sustainability to be an ethical and strategic imperative, and there has been a recent surge in employee interest in, and demand for, environmentally responsible practices from these institutions. Consequently, there has been a recent uptick in the amount of time and energy devoted to studying what motivates workers to engage in "green behavior," or acts that are good for the environment. In the preprocessing, tasks such as addressing missing data and applying min-max normalization are included. The optimal approach is min max. When it comes to feature selection, there are primarily two types of agents: those that provide appreciation and those that pick information. A method called BSP-CRF is used to train the model. The proposed method consistently outperforms the BSP and CRF models, boasting an accuracy level of 96.34%.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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