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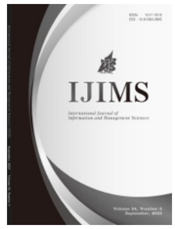

A Performance Key Features Analysis Model Based on Corporate Sustainability Micro-foundation and Machine Learning: An Empirical Study of the Fast Fashion Manufacturing Industry

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Keywords

Sustainability Dynamic Capability, Micro-foundation, Job Performance, Machine Learning, Ensemble Variable Selection Method.

Abstract

Organizations pursuing sustainable development need unique dynamic capabilities for complex business environments. Organizational dynamic capabilities are built on various forms of employee behaviors, thus possessing distinct individual micro-foundations. Job performance is a manifestation of an employee's behaviors aligned with organizational goals. Studying individual micro-foundations enhances the understanding of building organizational sustainability dynamic capabilities through their impact on job performance. This study collected multidimensional variables influencing job performance in the fashion manufacturing industry. By integrating machine learning techniques and ensemble variable selection methods, an analytical model was developed to identify key performance features. The empirical results revealed the top five key variables influencing job performance: previous year performance, tenure, age, interpersonal atmosphere, and hope. The study further explores these crucial variables and provides improvement recommendations for HR activities within the case company. These suggestions aim to facilitate a swift response to environmental changes and promote the development of dynamic capabilities for organizational sustainability.

1. Introduction

Sustainability pertains to the enduring development strategy adopted by organizations (Hart, 1995). The success of this approach depends on an organization's ability to continuously adapt to its environmental conditions, employing appropriate strategies to balance internal objectives with external demands. Organizations must establish distinct sustainability dynamic capabilities to achieve sustainable operation in response to different environmental shifts

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(Strauss et al., 2017). These capabilities are rooted in various forms of employee behaviors and possess unique individual-level characteristics, which form micro-foundations (Strauss et al., 2017).

Micro-foundations encompass the interactions between individuals and organizational processes and structures crucial to the development and formation of organizational capabilities (Felin et al., 2012). The micro-foundations approach aids in explaining how strategic dynamics are rooted in individual characteristics and behaviors. It is crucial to understand the phenomenon of organizational capabilities. Accordingly, the best comprehension is based on the micro level (Abell et al., 2008).

Employee behaviors link to the micro-foundations of developing sustainability dynamic capabilities. Organizations need employees who possess uniqueness, value, and non-imitability to support and achieve the development of sustainable competitive advantages (Kazlauskaitė & Bučiūnienė, 2008). Therefore, understanding the micro-foundations of employee behaviors and characteristics in an organization's response to the competitive environment and developing its sustainability dynamic capabilities will contribute significantly to the development of organizational sustainability.

Job performance reflects the measurement of an employee's actions or contributions to the organization (Campbell, 1990) and can be used to define the contribution of an employee's behavior to organizational goals (Waldman & Spangler, 1989). Therefore, comprehending the impact of individual characteristics on job performance contributes to understanding how employee behaviors support organizational goals and foster the development of sustainability dynamic capabilities.

Machine learning can construct effective classification models through various computer algorithms and collected data, providing crucial decision-making information. Prior studies also indicate that human resource management has gradually embraced machine learning, and related technologies have been widely applied across various professional domains in HR (Garg et al., 2022). Although recent developments in machine learning have extended to more complex and deeper learning methods, the research in this area remains predominantly technology-driven, with less emphasis on variable selection, the implications of models, and practical applications. The integration and practical application of machine learning with human resource management need further explored, necessitating more interdisciplinary collaboration between HR professionals and machine learning experts (Garg et al., 2022).

The fashion market is synonymous with rapid change. Its unique characteristics include highly variable products, highly subjective aesthetic evaluations, complex and lengthy manufacturing processes, short product life cycles, and a high degree of manual labor (Goto & Endo, 2014). Therefore, the success of the entire supply chain operation in the fashion industry largely depends on the organization's flexibility and rapid responsiveness. Furthermore, the fashion industry supply chain faces numerous sustainability issues, such as using water, energy, chemicals, and labor standards, including wages, child labor, occupational health, and working environment. Additionally, overconsumption of fashion apparel and end-of-life disposal behaviors significantly harm the environment. Many brands establish unique sustainability standards to effectively address these issues, enhance consumer perception, and improve brand image. The objective is to mitigate negative social and environmental impacts by enhancing control over supply chains, thereby imposing more rigorous sustainability challenges on the fashion industry supply chain.

This study focuses on the case of the fashion manufacturing industry, using corporate sustainability micro level as a foundation. It combines expertise in human resource management and machine learning through interdisciplinary collaboration. By conducting a literature review, it identifies essential characteristic variables that influence job performance. We develop a novel machine learning-based employee performance analysis model by applying an ensemble variable selection method. This model facilitates rapidly and effectively extracting crucial characteristic variables influencing job performance and enables organizations to swiftly comprehend individual characteristics affecting employee behaviors in highly dynamic competitive environments. Consequently, organizations can swiftly adjust their human resources decisions, aiding in the rapid adaptation necessary to construct their sustainability dynamic capabilities.

The structure of this paper is as follows: Section 2 is a literature review, which will discuss the correlation between organizational sustainability dynamic capabilities and job performance and examine research on individual characteristic variables related to job performance, as well as relevant studies on machine learning in performance prediction. Section 3 illustrates the employee performance analysis model based on machine learning proposed in this study. Section 4 presents the empirical results. The proposed model is applied to extract the crucial variables influencing individual job performance using data from a case company. Section 5 discusses practical operational recommendations based on the empirical results. Finally, Section 6 concludes the study and discusses its limitations while suggesting future research directions.

2. Literature Review

2.1. Organizational Sustainability Dynamic Capabilities and Their Micro-foundations

Sustainability is the strategic approach organizations adopt for long-term development (Hart, 1995). In sustainable development, organizations face economic, social, and environmental changes. They implement necessary measures and procedures to identify opportunities and mitigate risks, ultimately creating long-term value for the organization (Kocmanová et al., 2011). Previous studies have shown that in complex, competitive environments, organizations must go beyond regulatory requirements and possess a unique set of capabilities to navigate the dynamics of their environment (Aragón-Correa & Sharma, 2003). The proactive adoption of strategies by organizations to gain a competitive advantage originates from the Resource-Based View theory (Wernerfelt, 1984). Wernerfelt (1984) posited that organizational performance is the outcome of resource utilization, broadly defined as anything that represents an advantage or disadvantage relative to competitors, encompassing the organization's tangible and intangible assets.

Furthermore, Teece et al. (1997) extend the framework of dynamic capabilities to elucidate exceptional organizational performance in the face of a continuously changing environment. According to numerous scholars, dynamic capabilities are defined as repeatable patterns of organizational actions that allow an organization to develop its resource base and align it with the ever-changing demands of its environment (Eisenhardt & Martin, 2000; Teece et al., 1997). Therefore, dynamic capabilities emphasize an organization's ability to continuously adapt to dynamic environmental changes by reconfiguring, reallocating, and leveraging its resources and capabilities to generate exceptional performance.

Eisenhardt and Martin (2000) state that dynamic capabilities are the driving force behind exceptional performance, with their essence contingent on the market dynamism in which the organization operates. Aragón-Correa and Sharma (2003) further indicate that the dynamism of an organization's environment determines whether the organization develops proactive, adaptive strategies beyond regulatory requirements to gain a competitive advantage. Research results also demonstrate that the dynamic capabilities required by organizations vary across different market environments.

As mentioned earlier, the key to organizational sustainability lies in the organization's ability to continuously adapt to its environmental conditions by adopting appropriate strategies to develop the necessary dynamic capabilities, ultimately achieving sustainable operation, which involves the establishment of the organization's sustainability dynamic capabilities. According to Strauss et al. (2017), sustainability dynamic capabilities refer to the organization's capacity to reconfigure its resources in response to its sustainability strategy and environmental changes. These capabilities must balance the organization's goals with the demands of the external environment. The dynamism of the organizational environment is not solely influenced by external factors (exogenous) but is also partially generated by the organization's proactive environmental adaptation strategies (endogenous). From the perspective of Strauss et al., organizations need to develop different sustainability dynamic capabilities to respond to various environmental changes. These capabilities are based on various forms of employee behaviors, thus having different individual-level characteristics as their micro-foundations.

Micro-foundations are a crucial concept in organizational behavior theory, emphasizing that the behavior and performance of an organization can be traced back to the individual level of its members. In other words, micro-foundations focus on individuals' behavior, abilities, and motivations and their interactions with organizational processes and structures. These interactions at the individual level influence the development of organizational capabilities (Felin et al., 2012). Foss (1996) further underscores the significance of individual and team knowledge, skills, and resource allocation in organizational performance, illustrating that the sustainability dynamic capabilities of an organization rely on the micro-foundations of individuals and teams. Advocates of the micro-foundations approach argue that individuals are the origin of everyday activities and capabilities (Felin & Foss, 2005).

Additionally, Felin et al. (2012) emphasize that organizations need the capacity to deal with complexity and uncertainty, which emanates from the micro-foundations of organizational members, including their knowledge, skills, and adaptability. Effectively integrating the micro-foundations of members contributes to the realization of organizational goals. From this, it is evident that the micro-foundations approach involves individuals and considers how these elements aggregate. Organizational analysis should focus on how individual-level factors aggregate to the group level (Barney & Felin, 2013).

In summary, an organization adopting environmental adaptation strategies is contingent on environmental dynamism. This dynamism is not solely influenced by external factors but also partially generated by the organization's proactive and adaptive strategies. Therefore, research focused on individual-level characteristics contributes to understanding the development of organizational sustainability dynamic capabilities (Strauss et al., 2017). At the individual level, characteristics, behaviors, and interactions between individuals and organizational processes/structures are crucial for comprehending collective phenomena like an organization's everyday activities and capabilities.

2.2. Job Performance and Sustainability Dynamic Capabilities

Employee behaviors are related to the development of sustainability dynamic capabilities. Kazlauskaitė and Bučiūnienė (2008) firmly believe that to achieve and support the development of sustainable competitive advantages, organizations require employees who possess uniqueness, value, and non-imitability. Strategic scholars also argue that sustainable strategies are complex and require employee participation in the execution process (Etzion, 2007). Previous research has found that employee behaviors play a crucial role in the connection between organizational environmental adaptation strategies and their performance outcomes (Chen et al., 2015). Job performance defines employee behaviors' contribution to organizational goals (Waldman & Spangler, 1989). It reflects the measurement of actions and outcomes contributed by employees in the organization (Campbell, 1990). In this context, it becomes apparent that job performance not only serves as a direct manifestation of the contribution of employee behavior to organizational goals but also plays a pivotal role in fostering the development of sustainable competitive advantages and the cultivation of sustainability dynamic capabilities within the organization.

Regarding the variables influencing job performance, research indicates numerous factors, which can be broadly categorized into three main dimensions (Waldman & Spangler, 1989). Firstly, individual characteristics encompass variables such as education level, experience, abilities, and traits. The second dimension pertains to the work environment, such as supervisor leadership and interpersonal atmosphere. The third dimension concerns performance feedback, including rewards and job security. Therefore, a comprehensive understanding of how individual characteristics, behaviors, and the interactions between employees and the organizational environment and processes influence job performance can contribute to comprehending the contribution of employee behaviors to organizational goals. In turn, it facilitates the development of sustainability dynamic capabilities within the organization, utilizing a micro-foundation approach.

2.3. Machine Learning and Job Performance Prediction

Machine learning is an approach that is discovery-driven rather than hypothesis-driven. It involves exploring and analyzing collected data through various algorithms to discover meaningful patterns and rules. Continuous training enhances the performance of the established predictive or classification models, extracting rich information to support decision-making. Machine learning technology has been extensively applied and developed in various professional fields, with human resource management being one of them (Garg et al., 2022). Machine learning technology is also widely used in job performance prediction, with diverse applications and adoption methods across industries (Chou et al., 2022). These industries include government institution (Nasr et al., 2019), education (Kamatkar et al., 2018), finance (Sujatha & Dhivya, 2022), information technology (Al-Radaideh & Al Nagi, 2012), banking (Kamtar et al., 2019), and the garment industry (Wang & Shun, 2016). The adoption methods encompass support vector machines, decision tree approach, multiple regression approach, Naive Bayes classifier, Back Propagation Neural Networks, and eXtreme Gradient Boosting, among others. The primary process involves collecting personal characteristic information of relevant personnel (such as work experience, family status, educational background, and personality traits assessments) and behavior-related information during their tenure (such as job-related information and performance records). Through machine learning methods, performance prediction models are developed to reduce direct and indirect costs associated with recruitment, training, personnel maintenance, and talent retention. By examining the trends in recent years, the use of methods has evolved towards more sophisticated deep machine learning techniques. However, there is still a lack of integration of diverse information on the data front. If the limitations in data collection can be overcome, better research outcomes are expected.

Significant challenges exist in developing a sustainable human resource management knowledge system and integrating these practices into organizational management (Kramar, 2014). It requires interdisciplinary integration and the establishment of theory-based feedback between organizational actions and outcomes. Therefore, based on the theoretical foundations of past research, this study believes that a collection of essential variables influencing job performance, combined with deep machine learning techniques, can facilitate a comprehensive understanding of the relationship between individual variables and job performance. Exploring these aspects in-depth can serve as a reference for decision-making improvements. This micro-foundation approach makes a better understanding of organizational sustainability dynamic capabilities feasible and meaningful.

3. Employee Performance Analysis Model Based on Machine Learning

This study selects a case company that meets the sustainability measurement standards in the highly dynamic fashion industry. Important individual variables of employees in the company are collected. Five machine learning algorithms and an ensemble variable selection method construct an employee performance prediction model. It allows the exploration

and analysis of the collected data to discover meaningful patterns and rules, providing richer information and deeper insights. The proposed employee performance analysis model in this study is illustrated in Figure 1.

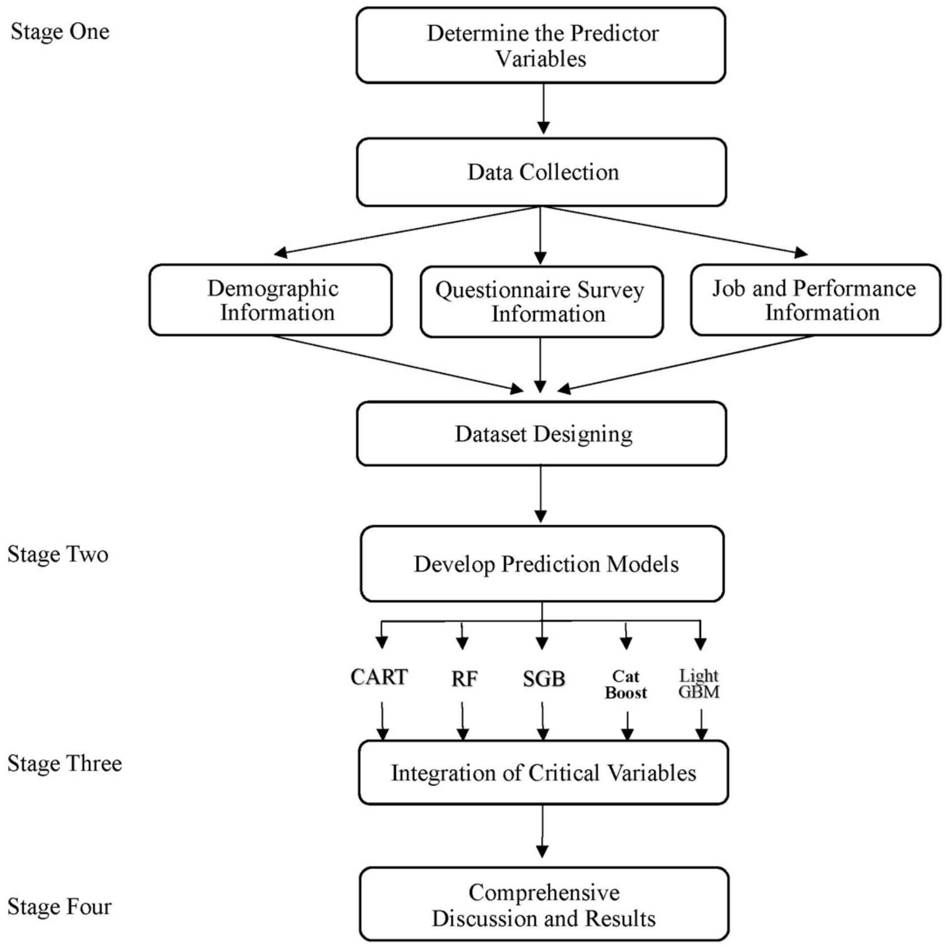

Figure 1 *The Employee Performance Analysis Model Based on Machine Learning Proposed in This Study*

3.1. Stage 1: Determining Predictor Variables, Data Collection, and Dataset Designing

This study comprises a total of twenty variables, including nineteen predictor variables and one target variable. The authors determined the individual variables that affect performance based on literature reviews and expert discussions. As mentioned earlier, variables influencing job performance can be broadly categorized into individual characteristics, work environment, and performance outcomes feedback. In the dimension of individual characteristics, this study uses nine predictor variables. In addition to age (X1-Age), which previous research has shown to be related to job performance (Saks & Waldman, 1998), education level (X4-EDU) (Ng & Feldman, 2009), and organizational tenure (X8-Tenure) (Ng & Feldman, 2009), we also included gender (X2-Gender) and marital status (X3-Married) as two variables. Personality traits have shown robust predictive effects on job performance (Judge et al., 2013). However, previous studies have shown that individual differences in psychological capital have a better predictive effect on job performance than traits like conscientiousness, extraversion, and neuroticism (Avey et al., 2011). Psychological capital refers to a person's positive psychological development, including four constructs: self-efficacy, hope, optimism, and resilience. Self-efficacy (X9-PSE) refers to the confidence to undertake and exert the necessary effort to accomplish challenging tasks. Hope (X10-PSH) is the ability to persevere toward goals and re-route as necessary to succeed. Optimism (X11-PSO) is defined as positive attributions about succeeding now and in the future. Resilience (X12-PSR) is demonstrated when facing problems and adversity, involving perseverance and even surpassing challenges to attain success (Luthans et al., 2007). Therefore, this study employs the four constructs of psychological capital as an additional four predictor variables in the dimension of individual characteristics.

The second dimension is work environment. This study uses job satisfaction and organizational identification as predictor variables in this dimension. Previous research has shown that job satisfaction and organizational identification are correlated with job performance (Carmeli et al., 2007; Jalagat, 2016). Job satisfaction consists of three constructs and three predictor variables. The first construct variable is basic elements (X13-JSA), aimed at understanding whether employees are satisfied with the stability of their work, workload, compensation, and the company's policy implementation. The second construct variable is supervisor leadership (X14-JSB), aimed at understanding whether employees are satisfied with how their supervisors treat, develop, and evaluate their subordinates. The third construct variable is interpersonal atmosphere (X15-JSC), primarily focusing on understanding whether employees are satisfied with establishing positive interpersonal relationships in their work environment, including collaboration, communication, and assistance to others. Organizational identification (X16-OI) is one variable primarily focused on understanding the identification and importance of employees towards the company's future development, reputation, and personal development. The third dimension is performance outcomes feedback. Performance outcomes feedback consists of three predictor variables, including the supervisor's assessment of performance (X17-Performance Y-1) and potential level (X18-Potential Y-1) and whether there was a promotion (X19-Promote Y-1) in the previous year. The last one is the target variable (Y-Performance), which is the actual performance assessment by supervisors for the current year. Through the above explanation, the 16 predictor variables comprehensively cover the three central dimensions of individual characteristics, work environment, and performance outcomes feedback. In addition, three additional predictor variables are included to facilitate potential future analysis, including department attributes (X5-Depts), position level (X6-Grade), and supervisor or not (X7-MGR). With this, the twenty variables used in this study have been confirmed. Among them, there are nineteen predictor variables and one target variable. Please refer to Table 1 for explanations of the twenty variables. The relevant information sources include personal data provided by employees (such as age, gender, marital status, and education level), questionnaire survey information (psychological capital, job satisfaction, and organizational identification), job-related information (such as department attributes, position level, supervisor or not, and organizational tenure), and supervisors' performance feedback to employees.

Table 1 *Variables, Data Source, Descriptions, and Descriptive Statistics*

Variables.	Data Source.	Descriptions.	Data type.	Continuous Variable: Mean ± Standard Deviation Categorical Variable: Percentage of Count
X1-Age	Demographic information	Age at the time of survey.	Numeric	36.33±8.41
X2-Gender		Male: 1, Female: 0.	Nominal	Male: 97(22.89%), Female: 327(77.12%)
X3-Married		Married: 1, Unmarried: 0.	Nominal	Married: 169(39.86%), Unmarried: 255(60.14%)
X4-EDU		Grouped as follows: Master's degree and above: 4, Bachelor's degree: 3 Associate degree: 2,High school and below: 1	Nominal	Master's degree and above: 101(23.82%), Bachelor's degree: 253(59.67%), Associate degree: 42(9.91%), High school and below: 28(6.60%)
X5-Depts	Job-related information	Divided into three groups: Sales and Marketing: A, Production Technology: B, Operations Support and Management: C.	Nominal	Sales and Marketing: 214(50.47%), Production Technology: 100(23.59%), Operations Support and Management: 110(25.94%)
X6-Grade		Position Level	Nominal	Grade 2: 5(1.18%), Grade 3: 147(34.67%), Grade 4: 137(32.31%), Grade 5: 84(19.81%), Grade 6: 34(8.02%), Grade 7: 12(2.83%), Grade 8: 5(1.18%)
X7-MGR		Supervisor: 1, Non-Supervisor: 0.	Nominal	Supervisor: 83(19.58%), Non-Supervisor: 341(80.42%)
X8-Tenure		Tenure in the company.	Numeric	7.55±5.92
X9-PSE	Questionnaire survey information	Self-efficacy: Measuring employees' confidence and belief in their ability to complete specific tasks or achieve specific goals successfully.	Numeric	3.75±0.49

X10-PSH	Questionnaire survey information	Hope: Measuring employees' willingness towards future goals and achieving them.	Numeric	3.67±0.46
X11-PSO		Optimism: Measuring the extent to which an employee's perspective on themselves and the future tends to be positive and optimistic.	Numeric	3.75±0.60
X12-PSR		Resilience: Measuring employee's resilience and adaptability when facing pressure, adversity, and setbacks.	Numeric	3.96±0.43
X13-JSA		Basic elements: Measuring employees' satisfaction with job stability, workload, compensation, and the implementation of company policies.	Numeric	3.49±0.53
X14-JSB		Supervisor leadership: Measuring employees' satisfaction with supervisors' treatment, developing, and performance evaluation.	Numeric	3.70±0.73
X15-JSC		Interpersonal atmosphere: Measuring employees' satisfaction with interpersonal relationships in their work environment.	Numeric	3.80±0.47
X16-OI		Organizational Identification: Measuring employees' identification with the organization and their willingness to actively continue participating.	Numeric	4.15±0.56
X17-Performance (Y-1)	Performance feedback information.	Performance assessment by supervisor in the previous year.	Nominal	Excellent: 81(19.10%), Good 1: 154(36.32%) Good 2: 172(40.57%), Improved: 17(4.01%)
X18-Potential (Y-1)		Potential assessment by supervisor in the previous year.	Nominal	High: 140(33.02%), Middle: 232(54.72%) Low: 52(12.26%)
X19-Promote (Y-1)		Promoted: 1, Not promoted: 0.	Nominal	Promoted: 157(37.03%), Not promoted: 267(62.97%)
Y-Performance		Performance assessment by the supervisor for the current year.	Nominal	Excellent: 92(21.70%), Good 1: 163(38.44%) Good 2: 153(36.09%), Improved: 16(3.77%)

After determining the variables, data collection and dataset designing were conducted. In addition to the demographic variables, job-related information, and performance feedback information initially possessed by the case company, this study conducted surveys on psychological capital, job satisfaction, and organizational identification. The questionnaire on psychological capital was based on the questionnaire designed by Luthans et al. (2007), which consists of four constructs: self-efficacy, hope, optimism, and resilience, with six items for each construct, totaling twenty-four items. The survey on job satisfaction used selected items from the Minnesota Satisfaction Questionnaire (Weiss et al., 1967), which included four questions on basic elements, three on supervisor leadership, and five on interpersonal atmosphere, making a total of twelve questions across three constructs. The organizational identification adopts four items from the scale developed by Cheney and Tompkins (1987). The items in all questionnaires are measured using the Likert 5-Point Scale, which includes the following ratings: Strongly Agree/Very Satisfied (5 points), Agree/Satisfied (4 points), Neutral (3 points), Disagree/Dissatisfied (2 points), and Strongly Disagree/Very Dissatisfied (1 point). Participants are required to select one of the five options based on their agreement level (for psychological capital and organizational identification questionnaires) or satisfaction level (for job satisfaction questionnaire) after each item. A total of 495 responses were collected. Since this study conducted a performance prediction analysis for the following year, 73 employees who left during the period were excluded. It resulted in a total of 424 valid samples for analysis. After a reliability analysis, all item factor loadings were above 0.5(Hair et al., 2006).

Additionally, internal consistency reliability within each construct was examined. Five items were removed to enhance internal consistency reliability: three on optimism in psychological capital and two on resilience. The Cronbach's α for all constructs exceeded 0.7 (George, 2011), indicating high internal consistency. For details on the items, factor loadings, excluded items, and Cronbach's α values, please refer to Table 2.

Table 2 *Overview of the Number of Items, Deleted Items, Interval of Factor Loadings, and Cronbach's a Values for Each Construct of This Study*

Constructs	Number of Survey Items	Number of Deleted Items	Interval of Factor Loading	Cronbach'α Value
X9-PSE	6	0	.769 ~ .803	.816
X10-PSH	6	0	.761 ~ .811	.812
X11-PSO	6	3	.762 ~ .861	.860
X12-PSR	6	2	.728 ~ .805	.806
X13-JSA	4	0	.620 ~ .693	.723
X14-JSB	3	0	.829 ~ .879	.897
X15-JSC	5	0	.689 ~ .762	.766
X16-OI	4	0	.797 ~ .830	.854

With this, dataset for all 20 variables have been completed. The next step will involve developing the performance prediction model and conducting data analysis using this dataset.

3.2. Stage 2: Develop Prediction Models

The subsequent step will entail developing the performance prediction model using this dataset. This study adopts five decision tree-based classification techniques, namely CART (Classification and Regression Tree), RF (Random Forest), SGB (Stochastic Gradient Boosting), CatBoost (Categorical Boosting), and LightGBM (Light Gradient Boosting Machine). Due to their modeling processes that can simultaneously provide information on crucial variable selection, these techniques effectively identify critical individual features influencing job performance.

CART, proposed by Breiman et al. (1984), is a decision tree technique based on a recursive algorithm that explores the data structure and produces decision rules that are easy to visualize, facilitating the construction of predictive classification or regression models. CART models exhibit good rule interpretability, allowing the determination of the importance of predictor variables by understanding the reduction in error associated with the target variable (Timofeev, 2004).

RF, introduced by Breiman (2001), is an ensemble learning algorithm based on decision tree classifiers. In a typical RF, the classifier is CART. The Bagging procedure chooses multiple random samples as training datasets to reduce variance and help prevent overfitting. During the data training process, a large number of classification trees corresponding to the selected samples are constructed to form the RF. Finally, all classification trees are combined, and each category is voted on. The winning category is selected based on the vote count to obtain the final classification results.

SGB is the random version of the standard gradient boosting algorithm inspired by Friedman (2002) based on the approach of adaptive bagging proposed by Breiman (1999). It introduces the idea of bootstrapping the entire dataset, adding randomness to the tree-building process. In each iteration of the boosting process, SGB's sampling algorithm selects random objects, effectively reducing the complexity of each iteration.

CatBoost is a gradient boosting decision tree technique explicitly designed for datasets with categorical features. It combines sequential boosting with gradient boosting methods, aggregating the tree combinations and categorical features generated into a sequence to create the final model (Dorogush et al., 2018). CatBoost possesses powerful classification capabilities, directly handling categorical features, automatically managing missing values, avoiding overfitting, and providing excellent model interpretability.

LightGBM is a distributed gradient boosting framework based on decision trees. It leverages advanced histogram techniques, allowing it to quickly learn the approximate values of decision tree residuals through one-sided sampling and negative gradient fitting in each iteration (Ke et al., 2017). LightGBM often achieves superior performance on the same dataset and training time than other gradient boosting methods.

This study constructed five predictive models incorporating CART, RF, SGB, CatBoost, and LightGBM for subsequent model information integration and comparison. The modeling process was conducted using R software version 3.6.2 and R Studio software version 1.1.453 (http://www.R-project.org, accessed on 1 September 2022; https://www.rstudio.com/products/rstudio/, accessed on 1 September 2022). Each model was constructed using R-based packages.

Specifically, CART utilized version 4.1-19 of the "rpart" package (Therneau et al., 2022). RF employed version 4.7-1.1 of the "randomForest" package (Breiman et al., 2022). SGB used version 2.1.8 of the "gbm" package (Greenwell et al., 2020). CatBoost and LightGBM used versions 0.25.1 (YandexTechnologies., 2022) and 3.3.2 (Microsoft, 2022).

In the model construction process, version 6.0-93 of the "caret" package was used to search for the optimal hyperparameter combinations for each model (Kuhn, 2022). For modeling, the entire dataset was randomly divided into 80% training data and 20% testing data. Hyperparameter tuning for each model involved 10-fold cross-validation.

As this study is predictive research focusing on four performance categories, accuracy is employed as the performance indicator for the predictive models. A higher accuracy indicates better model performance.

3.3. Stage 3: Integration of Critical Variables

The third stage involves the identification of essential variables influencing job performance. An ensemble variable selection method is employed to enhance variable selection performance and overcome the limitations of a single machine learning technique. This approach combines different weak learner models to improve overall accuracy. The Borda count method (Polikar, 2006) ranks the variable selection results produced by combining different methods, providing a unified selection outcome. In this stage, the independently learned predictor variables from the previous stage are ranked based on their importance. The ranking values of important predictor variables from various methods are then summed and averaged. Finally, the overall ranking of predictor variables is determined based on the averaged values, yielding the final ranking of the key variables influencing job performance of the year.

3.4. Stage 4: Comprehensive Discussion and Results

The fourth stage involves exploring the individual characteristic variables that influence job performance. In this stage, the discussion will be guided by the principle of importance, constructing a profile of significant individual features within the case company that impact employee job performance. This profile serves as a basis for human resources decision-making reference.

4. Empirical Study

4.1 Background of the Case Company

The case company, founded in 1990, is a leading player in the fashion industry in Taiwan. It caters to a diverse clientele, including well-known global brands, department stores, and retailers across the Americas, Europe, and Asia. Headquartered in Taipei, Taiwan, the company has established its services and manufacturing facilities in six countries: Vietnam, Indonesia, Cambodia, China, the Philippines, and Lesotho. The company exhibits excellent competitiveness with a strong presence in the global market.

The company has consistently demonstrated long-term solid performance and is selected as a component stock of the Fubon Taiwan Corporate Governance 100 Fund. Additionally, it is included in the Yuanta ESG Low Carbon High Dividend ETF 00930, which proves its profitability and robust corporate governance capabilities with a commitment to low carbon and

ESG principles. Given its commendable financial performance and governance practices, the case company is a suitable subject for this research.

4.2. Empirical Results

In this study, a total of 424 employee records from the case company were collected. The participants exhibited an average age of 36.33 years, with a predominant female representation at 77.12% and 60.14% unmarried. In terms of education, a majority possessed a bachelor's degree (59.67%), while 23.82% held a master's degree or higher. The Sales and Marketing department accounted for 50.47%, and non-supervisory staff represented 80.42%. For detailed distribution information on other variables, please refer to Table 1.

The predictive models constructed using the five machine learning methods in this study demonstrated accuracy levels ranging from 51.76% to 63.53%. Notably, the CatBoost model achieved the highest accuracy at 63.53%. Considering the four-category predictive model, this indicated a favorable predictive performance. The accuracy of each predictive model is detailed in Table 3.

Table 3 *Accuracy of Predictive Models for Five Machine Learning Methods*

Methods	Accuracy
CART	51.76%
RF	60.00%
SGB	54.12%
CatBoost	63.53%
LightGBM	55.29%

In addition to evaluating the accuracy of each method, the importance of each variable in different models was ranked, yielding valuable insights for identifying significant variables. This study employed the Wrapper method from the "caret" R package Version 6.0-93(Kuhn, 2022) to conduct the ranking. The most critical predictor variables were assigned a ranking of 1, with higher rankings indicating lower importance of the predictor variable. After ranking the variables based on their relative importance across the five machine learning models, X17-Performance(Y-1) and X8-Tenure emerged as the most crucial variable influencing job performance. The third to fifth most essential variables were X1-Age, X15-JSC, and X10-PSH, respectively. Please refer to Table 4 for the importance rankings of the remaining variables. Subsequent discussions will adhere to the principle of importance for managerial applications, delving into the top five variables influencing job performance.

Table 4 *Relative Importance Ranking of Variables and Overall Ranking Summary for the 5 Machine Learning Methods*

Variables	Average Ranking of CART	Average Ranking of RF	Average Ranking of SGB	Average Ranking of CatBoost	Average Ranking of LightGBM	Sum Average Ranking	Ranking
X1-Age	4	3	3	4	2	3.2	3
X2-Gender	19	16	19	18	18	18	19
X3-Married	11	17	18	16	17	15.8	16
X4-EDU	14	14	15	15	15	14.6	15
X5-Depts	17	15	14	12	14	14.4	14
X6-Grade	12	13	12	14	13	12.8	13
X7-MGR	15	19	16	19	19	17.6	18
X8-Tenure	3	2	2	2	1	2	1
X9-PSE	7	7	7	6	8	7	7
X10-PSH	5	6	9	3	4	5.4	5
X11-PSO	10	10	10	11	10	10.2	10
X12-PSR	13	12	13	13	11	12.4	12
X13-JSA	9	8	6	10	5	7.6	9
X14-JSB	8	5	5	7	7	6.4	6
X15-JSC	2	4	8	8	3	5	4
X16-OC	6	9	4	9	9	7.4	8
X17-Performance (Y-1)	1	1	1	1	6	2	1
X18-Potential (Y-1)	16	11	11	5	12	11	11
X19-Promote (Y-1)	18	18	17	17	16	17.2	17

5. Discussion

The study provided insightful findings regarding the factors that influenced job performance. In exploring the variables influencing job performance, X17-Performance(Y-1) and X8-Tenure emerged as the most critical in this study, ranking first in importance. We first discuss X17-Performance(Y-1).

Job performance is expressed as a multiplicative function of job knowledge and skill, effort, and resources/constraints, and it interacts to impact performance (Blumberg & Pringle, 1982).

Job performance can be conceptualized as an ongoing process over time, such that current performance, to some extent, reflects past performance (Ilgen et al., 1979).

This study analyzed performance ratings from the previous year and performance distribution in the subsequent year. The results of the chi-square test indicated a statistical significance in the distribution of performance ratings between the previous year and the subsequent year ($\chi^2=217.462$, $p<.001$). Therefore, for the case company, the management focus could be improving the performance of employees lagging. Feedback is a crucial aspect of performance improvement, which can help employees focus their efforts more effectively. Feedback is defined as information sent to the recipient about their behavior, and returning this information to an individual's belief or knowledge systems influences subsequent effort and performance (Chhokar & Wallin, 1984).

Waldman et al. (1987) found that different aspects of feedback are related to individuals' trust and satisfaction with their performance assessment system. Individuals are more satisfied with feedback used to recognize achievements and are oriented towards development. Conversely, feedback to correct negative performance anomalies and errors is the least satisfying. Specific feedback leads to better performance than general feedback (Earley, 1988). Therefore, the case company could focus on improving the performance assessment system to enhance employee trust and satisfaction. Additionally, training supervisors in performance feedback techniques, emphasizing specificity and a developmental orientation, could effectively assist employees in performance improvement.

Table 5 *Contingency Table of X17-Performance(Y-1) by Y-Performance*

		Y-Performance				
X17-Performance(Y-1)		E	G1	G2	I	Total
E	Count	51	24	5	1	81
	% within row	62.96%	29.63%	6.17%	1.24%	100%
G1	Count	32	90	32	0	154
	% within row	20.78%	58.44%	20.78%	0.00%	100%
G2	Count	9	47	106	10	172
	% within row	5.23%	27.33%	61.63%	5.81%	100%
I	Count	0	2	10	5	17
	% within row	0.00%	11.77%	58.82%	29.41%	100%
Total	Count	92	163	153	16	424
	% within row	21.70%	38.44%	36.09%	3.77%	100%

* $\chi^2(9,N=424)=217.462$, $p<.001$

The variable also ranking first was X8-Tenure. Organizational tenure has long been a significant research topic in understanding job performance. Previous studies have indicated that employees with longer organizational tenure generally exhibit better job performance, even after controlling for age. Additionally, research suggests a curvilinear relationship between organizational tenure and job performance. Although there is a generally positive trend, the strength of this relationship tends to weaken as organizational tenure increases (Ng & Feldman, 2010).

The findings of this study also indicated that tenure is a crucial variable influencing job performance. We further analyzed the mean of age and performance categories. As shown in Table 6, the average tenure for the highest performing group E was 6.75, followed by 7.11 for G1. The underperforming groups G2 and I had average tenures of 8.45 and 8.03, respectively. The average tenure was 7.55, indicating that individuals with above average tenure exhibited decreased performance. This finding underscored the importance of organizations adjusting their human resources strategies based on employees' tenure. In the early stages of employment, the focus should be on promoting employee integration into the organization to reduce talent turnover. As employees' tenure increases, efforts should shift toward enhancing employee motivation and skills to prevent a decline in job performance, making it a focal point for human resource management.

Table 6 *Mean of X8-Tenure and X1-Age Across the Four Categories of Annual Performance*

Variables / Mean of Performance	E	G1	G2	I	Overall
X8-Tenure	6.75	7.11	8.45	8.03	7.55
X1-Age	34.60	35.37	38.33	36.94	36.33

X1-Age was the third important variable affecting job performance. Previous study found that individual performance tends to increase with age, but these ratings gradually decline as age increases (Waldman & Avolio, 1986). The findings of this study also indicated that age is a crucial variable influencing job performance. We further analyzed the mean of age and performance categories. As shown in Table 6, the average age for group E was 34.60, followed by 35.37 for G1. The underperforming groups G2 and I had average ages of 38.33 and 36.94, respectively. The average age was 36.33, indicating that individuals above average exhibited decreased performance. This finding underscored the importance of organizations adjusting their human resources strategies based on employees' age. However, previous research has also found that although there is an association between age and job performance, special attention must be paid to the type of work (professional vs. non-professional) and the impact of work experience (Waldman & Avolio, 1986). Professionals (such as researchers and managers), due to the stimulation of aging and the constantly changing work environment, can often take on new and challenging leadership roles, leading to sustained or even job performance growth. On the other hand, non-professionals (such as laborers and general administrative staff) may face a less stimulating work environment, potentially resulting in stagnation and declining performance as they age. Quińones et al. (1995) also found in their meta-analysis that the quantity and task level of work experience highly correlate with job performance. Therefore, despite the negative association between age and job performance in middle and old age (Avolio et al., 1990), the case company should still pay special attention to the type of work (professional vs. non-professional) and the role of work experience in its human resources policies. For professional roles, dispelling age-related myths is crucial. Sustaining a stimulating work environment with opportunities for promotion or new task assignments may foster continuous growth in job performance. Particularly for non-professional workers, offering appropriate stimulation, such as training and job rotations, helps in maintaining or enhancing employee job performance and preventing decline. Moreover, the rapid manifestation of job performance with accumulated work experience, particularly in challenging tasks, diminishes the significance of age as a concern for job performance. Consequently, the case company should adapt its personnel decision-making considerations.

Occupying the fourth position in importance was X15-JSC, referring to the interpersonal atmosphere. This variable primarily assessed employees' satisfaction with establishing positive interpersonal relationships in their work environment involving collaboration, communication, and assistance to others.

The comprehensive model of individual job motivation illustrates that job motivation, job performance, and job satisfaction are interdependent and interactive variables (Schermerhorn Jr et al., 2011). They form a cyclical process rather than a linear one. Herzberg's two-factor theory also emphasizes the importance of interpersonal relationships and recognition from others in job satisfaction or dissatisfaction. Therefore, improving the interpersonal atmosphere can contribute to the mutual interaction of job motivation and performance.

Importance-performance analysis (IPA) is a technique widely used to identify product or service quality attributes that most need improvement. The concept was introduced by Martilla and James (1977). Slack (1994) further suggested that IPA is applicable for assessing competitive factors that influence organizational performance, enabling the prioritization of these factors for internal improvement. We further apply the IPA concept to cross-analyze the average scores of each item in the JSC construct with the performance categories and aim to identify the priority areas for human resources improvement. Further analysis of the five items in this construct is shown in Table 7. The cross-analysis of the five items and performance categories showed that high performers (E) had higher satisfaction in items 1, 3, and 5 compared to other performance categories and the overall average. However, item 2 showed the opposite trend. Therefore, despite item 2 having the lowest average satisfaction, it was not the priority for improvement. In items 1 and 3, the satisfaction of lower performers (G2, I) were even higher than the overall average, indicating other priorities for improvement. As a result, the case company should prioritize improvement in item 5 (The opportunity to guide and advise others in the workplace). The company may prioritize allocating resources to promote the demonstration of employee value and recognition by others. Doing this should contribute to an increase in job satisfaction, thereby influencing work motivation and performance.

Table 7 *The Cross-Analysis of the X15-JSC Items and Performance Categories*

Performance/ Mean of Items	JSC-01	JSC-02	JSC-03	JSC-04	JSC-05
E	4.10	3.50	4.00	3.88	3.87
G1	3.94	3.45	3.85	3.78	3.74
G2	4.01	3.57	3.87	3.88	3.78
I	4.00	3.63	3.94	3.63	3.63
Overall	4.00	3.51	3.89	3.83	3.78

The variable ranked fifth was X10-PSH (hope), which belongs to the psychological capital construct. The findings of this study aligned with previous research, demonstrating that psychological capital has an excellent predictive effect on job performance (Avey et al., 2011). Research indicated that individuals with high levels of hope were better equipped to cope with obstacles, having multiple alternative routes to navigate or circumvent the stress and negative emotions associated with setbacks (Snyder, 2002). Research also indicated that leadership played a crucial role in fostering followers' psychological capital (Avey et al., 2011), and psychological capital can be enhanced through developmental interventions (Luthans et al., 2010).

To identify priority areas for improvement, we conducted a further cross-analysis of the six items in X10-PSH construct and performance categories. The analysis from Table 8 reveals that high performers (E) did not score higher than relatively lower performers in items 2, 3, 4, and 6, indicating that these were not priority areas for improvement. However, in item 1 (When I found that my performance appraisal was less than the expected goal, I am trying to find ways to improve, and then start to do better.) and item 5 (When I set goals and plan to work, I will be concentrated to achieve the goal.), high performers had higher averages than lower performers. Therefore, the case company should prioritize allocating resources to improve these two areas, mainly by training leaders. The development of subordinates' psychological capital can be facilitated through management interventions and guidance from leaders to enhance their performance.

Table 8 *The Cross-Analysis of the X10-PSH Items and Performance Categories*

Performance/ Mean of Items	PSH-01	PSH-02	PSH-03	PSH-04	PSH-05	PSH-06
E	3.87	3.84	4.23	3.46	3.68	3.23
G1	3.77	3.69	4.20	3.50	3.65	3.23
G2	3.75	3.65	4.16	3.41	3.62	3.28
I	3.69	3.94	4.25	3.50	3.56	3.19
Overall	3.78	3.72	4.19	3.46	3.64	3.25

Furthermore, looking at the three major perspectives of variables influencing job performance, the individual characteristic accounted for five out of the top ten variables: X8-Tenure (ranking 1), X1-Age (ranking 3), X10-PSH (ranking 5), X9-PSE (ranking 7) and X11-PSO (ranking 10). The work environment included four variables: X15-JSC (ranking 4), X14-JSB (ranking 6), X16-OI (ranking 8), and X13-JSA (ranking 9). The performance feedback perspective contributed the most important variable: X17-Performance(Y-1) (ranking 1). The results illustrated the significant impact of variables from each perspective on job performance.

6. Conclusion and limitations

To ensure sustainable operations in a highly dynamic environment, organizations must demonstrate prompt responsiveness to customer demands and adeptly navigate sustainability challenges. The crux of the matter revolves around the ability of organizations to establish effective sustainability dynamic capabilities to address environmental changes, with human resource management assuming a pivotal role in this process. This study integrates human resources expertise with machine learning techniques to facilitate organizations in identifying essential individual features in the construction of sustainability dynamic capabilities. We have developed a rapid and effective analysis model. By collecting and analyzing internally organized human resources information inside the company, organizations can expeditiously comprehend the fundamental factors influencing individual performance and tailor their human resource activities accordingly. Organizations can use this analysis model as a foundation, continually adjusting and collecting internal information that may impact individual performance, enabling rapid responses to the business environment and maintaining their dynamic capabilities to achieve sustainability goals.

Last, there are several limitations in this research. Firstly, there is a limitation in the completeness of the factors. Some variables impacting individual job performance are not discussed, such as work motivation, personal knowledge and skills, job complexity, resource constraints, and information regarding the influence of groups and organizational levels. Secondly, only five machine learning techniques are employed in the study, and as such, the results may represent a relatively optimal solution. Future research should focus on addressing these limitations to achieve a more comprehensive study.

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