A Hybrid PCA–Random Forest Model for Predicting Employee Performance from Work Ethics and Work Values

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***Abstract*—This study examined the predictive relationship of work ethics and work values with employee task performance using a hybrid PCA–Random Forest model. Data were obtained from 231 PSU employee respondents and 81 questionnaire variables covering task performance, work ethics, and work values. A quantitative, cross-sectional predictive design was used; therefore, the findings are interpreted as predictive associations rather than causal effects. Descriptive statistics, reliability analysis, correlation analysis, Principal Component Analysis (PCA), baseline regression models, Random Forest regression, and a hybrid PCA–Random Forest model were applied. PCA reduced the 74 predictor items into 19 components, explaining 80.9% of the predictor variance. On the held-out test set, the hybrid PCA–Random Forest model achieved MAE = 0.272, RMSE = 0.383, and R^2 = 0.524. Standard Random Forest produced a similar test performance (MAE = 0.283, RMSE = 0.383, R^2 = 0.526), indicating that PCA did not substantially improve accuracy but produced a more compact and less redundant feature representation. Professionalism, commitment to public interest, and nationalism and patriotism emerged as important predictors of task performance. The study demonstrates the usefulness of interpretable machine-learning models for evidence-based human resource development in public higher education, while noting limitations related to ceiling effects, self-report data, single-institution sampling, and the need for external validation.**

***Keywords*—Employee performance; work ethics; work values; principal component analysis; random forest; hybrid model; machine learning; PSU employees**

I. Introduction

Employee performance is a critical concern in public sector institutions because the quality of public service depends largely on how effectively employees perform their duties. In state universities, employee performance is commonly reflected in task completion, timeliness, efficiency, and quality of outputs, all of which directly affect institutional effectiveness and stakeholder satisfaction. In the present study, employee performance is operationalized through task performance indicators such as planning work on time, accomplishing tasks efficiently, and producing quality outcomes, while work ethics and work values are treated as key explanatory factors.

Work ethics and work values are particularly important in the context of public employment because they shape employees' sense of accountability, professionalism, integrity, responsiveness, and commitment to the public interest. Ethical conduct and values-based behavior influence not only how employees carry out assigned responsibilities but also how they interact with clients, colleagues, and the organization as a whole. Prior studies have shown that workplace attitudes and behavioral factors are significantly related to task performance and work outcomes [1], while innovative work behavior and citizenship-related behavior also contribute to stronger workplace contribution and effectiveness [2]. In addition, job satisfaction and work engagement have been linked to desirable organizational outcomes and reduced turnover intention, suggesting that employee values and work orientation play a meaningful role in performance-related behavior [3].

Despite the recognized importance of work ethics and work values, modeling their relationship with employee performance remains methodologically challenging. These constructs are usually measured through multiple Likert-scale items, making them inherently multidimensional and often highly correlated. Traditional statistical methods remain useful for explanation, but they may be limited in capturing nonlinear relationships and interaction effects among behavioral variables. Recent work has emphasized that machine learning models are increasingly suitable for the social sciences because they can handle complex and nonlinear associations more effectively than strictly linear techniques [4], [5]. Best-practice discussions in psychological and behavioral machine learning further note that supervised learning methods can strengthen prediction when data preparation, validation, and interpretation are conducted rigorously [6].

In psychometric and survey-based studies, the quality of indicators strongly affects model performance and interpretability. Multivariate measurement research has long emphasized that the selection and treatment of indicators can substantially influence modeling outcomes [7]. This is particularly relevant in employee studies where ethics, values, and performance are each represented by multiple observed variables rather than by a single direct measure. Psychometric evaluation studies also demonstrate the importance of sound measurement properties in survey-based research [8], [9]. For this reason, any predictive study involving questionnaire data should pay careful attention to the structure, redundancy, and quality of indicators before model construction.

Another major concern in survey-based modeling is data quality. Missing responses, careless answering, and meaningless response patterns may reduce the reliability of results if left untreated. Missing data have been identified as a key issue in survey research, with consequences for estimation quality, validity, and interpretation [10]. Likewise, nonreactive

indicators can help identify poor-quality or meaningless responses in self-report surveys [11]. Because the present study relies on multiple questionnaire items measuring work ethics, work values, and task performance, careful preprocessing is necessary to ensure that the predictive model is based on valid and stable information.

Given the large number of survey indicators, dimensionality reduction becomes a practical necessity. Principal Component Analysis (PCA) is a widely used technique for transforming correlated variables into a smaller number of components while preserving as much information as possible. This approach is especially useful when many predictors overlap conceptually and statistically, as is common in behavioral and organizational datasets [7], [12]. By reducing redundancy and multicollinearity, PCA can improve the efficiency of downstream predictive models and simplify interpretation at the component level. In multivariate research, such reduction techniques are valuable when latent structures must be approximated from many observed indicators [13].

After dimensionality reduction, Random Forest is an appropriate predictive algorithm for employee performance because it can accommodate nonlinear relationships, higher-order interactions, and complex variable patterns without strict distributional assumptions. Machine learning research in psychometrics and the social sciences has shown that such methods are particularly advantageous when the goal is prediction rather than only parameter estimation [4], [5], [6]. Random Forest is also robust for structured tabular data and can perform well in moderate-sized datasets such as employee survey data. Since work ethics and work values may influence performance in nonuniform ways across respondents, an ensemble-based learner such as Random Forest is a suitable modeling choice.

A further strength of Random Forest is its compatibility with model interpretation tools. In applied organizational research, predictive accuracy alone is insufficient; decision makers also need to understand which factors are driving model predictions. Interpretable machine learning frameworks provide ways to explain black-box models and support evidence-based decision-making [14]. Feature attribution methods such as Shapley-based explanations can be used to estimate the contribution of individual predictors or components to model output [15], [16]. This is especially valuable in the present study because it allows the identification of which ethical and value-based dimensions are most strongly associated with employee performance.

Model evaluation is also essential in determining whether a predictive framework is appropriate and defensible. Comparative assessment using established evaluation metrics is recommended in machine learning studies to ensure that predictive performance is examined systematically and transparently [17]. In social science applications, methodological rigor likewise requires proper training-validation procedures and responsible reporting of predictive results [6]. Consequently, the adoption of a hybrid model should not only be justified conceptually but also supported empirically through relevant performance measures.

The use of a hybrid PCA–Random Forest framework is therefore justified both statistically and substantively. Statistically, PCA addresses the high dimensionality and multicollinearity common in questionnaire-based predictors, while Random Forest captures nonlinear patterns that may exist between employee ethics, values, and task performance [4], [7], [12]. Substantively, the model supports a more data-driven understanding of how employee characteristics translate into work outcomes in a public university setting. Related studies have shown that work-related attitudes, engagement, and behavioral orientations are connected to performance, satisfaction, and organizational contribution [3], [18], [19]. These findings reinforce the importance of examining performance not only as a function of technical capacity but also as an outcome associated with ethical and value-based dimensions of work.

The present study is also timely because organizational environments are becoming increasingly data-driven, requiring more robust methods for analyzing human-centered workplace data. Machine learning has gained growing relevance in social and behavioral inquiry because it can complement conventional methods in identifying predictive structures from complex datasets [4]. Tutorials and methodological reviews likewise encourage the careful adoption of supervised machine learning in psychology and related disciplines to enhance predictive validity and methodological innovation [17]. In this regard, the proposed hybrid model contributes to the emerging application of machine learning in educational and public sector workforce studies.

Accordingly, this study proposes A Hybrid PCA–Random Forest Model for Predicting Employee Performance from Work Ethics and Work Values among Employees. Specifically, it seeks to determine whether the multidimensional indicators of work ethics and work values can be reduced into meaningful components and used to predict employee task performance with acceptable accuracy and interpretability. By integrating survey-based measurement, dimensionality reduction, ensemble learning, and interpretable machine learning, the study contributes both a methodological approach and an applied perspective for understanding employee performance [14].

Although previous studies have established associations between work-related attitudes, values, engagement, and performance, much of the existing literature remains descriptive or correlational. Fewer studies have examined whether multidimensional work ethics and work values indicators can predict employee performance using a transparent machine-learning framework. In addition, many predictive studies emphasize accuracy but provide limited interpretation of the psychological or organizational meaning of model features. This creates a gap for an approach that combines dimensionality reduction, nonlinear prediction, and interpretability. The present study addresses this gap by evaluating whether PCA-derived dimensions of work ethics and work values can be used in a Random Forest model to predict task performance among public university employees. Ultimately, the findings may provide evidence-based support for institutional strategies aimed at strengthening employee effectiveness through ethics- and values-oriented development.

II. METHODOLOGY

This section presents the research design, data sources, and analytical procedures used in the study. It describes how the predictor variables were measured and how the six regression models were developed and compared to determine the most appropriate approach for analyzing the relationships among the variables.

A. Research Design

This study employed a quantitative, cross-sectional, predictive research design. The objective was to develop and evaluate a hybrid PCA–Random Forest model for predicting employee performance from work ethics and work values among Pangasinan State University (PSU) employees. The predictive framework was selected because machine learning methods are well suited for social science data with many correlated variables and potentially nonlinear relationships. The hybrid design combined Principal Component Analysis (PCA) for feature reduction with Random Forest Regression for prediction, a combination that is appropriate when survey-based predictors are numerous, overlapping, and multidimensional. The study was explanatory-predictive in nature. It not only describes the levels of work ethics, work values, and employee performance, but also models how ethics- and value-related indicators jointly predict task performance. This design is consistent with current recommendations that machine learning in behavioral and psychometric research should be used to complement traditional explanatory approaches through rigorous preprocessing, validation, and interpretable modeling. The study is therefore best interpreted as a predictive and exploratory model of performance-related patterns within the PSU employee sample.

B. Data Source and Unit Analysis

The dataset used was taken from the survey of PSU employees, which contains 231 respondent records and 81 item-level variables corresponding to the questionnaire dimensions. The unit of analysis was the individual PSU employee respondent. The predictor set consisted of work ethics and work values items, while the outcome variable was employee task performance derived from the task productivity indicators in the questionnaire. The questionnaire is composed of three major parts. Part I measures task performance through seven indicators (pro1–pro7) using a 5-point agreement scale. Part II measures work ethics using multiple indicators across eight dimensions: commitment to public interest, professionalism, political neutrality, justness and sincerity, responsiveness to the public, nationalism and patriotism, commitment to democracy, and simple living. Part III measures work values across six dimensions: God-fearing, accountability, integrity, transparency, innovativeness, and competency. These constructs and response formats are explicitly defined in the uploaded instrument.

Because the data were collected through self-report questionnaires, the findings may be affected by common-method bias and socially desirable responding. This concern is particularly relevant because ethics and values are socially valued constructs. The results should therefore be interpreted as respondents' reported perceptions of their work behavior and values rather than as direct administrative performance records.

C. Research Locale and Population

The study focused on PSU employees as reflected in the survey instrument. The target population, therefore, consisted of PSU personnel who responded to the questionnaire. The study treated the dataset as the empirical basis for training and evaluating the predictive model.

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D. Instrumentation and Variable Operationalization

Employee performance was operationalized as task performance, based on the seven indicators in Part I of the questionnaire: planning work on time, optimal planning, distinguishing major from minor issues, performing work with minimal time and effort, completing tasks efficiently, producing high-quality outputs, and keeping intended results in mind. These seven indicators were rated on a 5-point Likert-type scale and were combined to form the target construct for prediction.

The predictor variables were drawn from Parts II and III of the questionnaires. The work ethics construct includes the following dimensions and item groups: commitment to public interest (com1–com7), professionalism (prof1–prof7), political neutrality (po1–po4), justness and sincerity (j1–j5), responsiveness to the public (res1–res6), nationalism and patriotism (na1–na6), commitment to democracy (co1–co3), and simple living (sim1–sim6). The work values construct includes God-fearing (god1–god5), accountability (acc1–acc5), integrity (in1–in5), transparency (tra1–tra5), innovativeness (inno1–inno5), and competency (compe1–compe5, including the dataset's comp3 field corresponding to the third competency item). These domains and items are specified in the questionnaire. All predictors were treated as ordinal Likert-type responses coded numerically from 1 to 5. In practice, Likert item responses are commonly modeled as numeric inputs in psychometric and supervised learning workflows, particularly when the goal is prediction rather than purely ordinal inference.

E. Data Preparation and Screening

Fig. 1 shows the data preprocessing and screening flowchart. The dataset was screened for completeness, correct variable names, duplicate cases, and valid response ranges. Because all questionnaire items used a 1–5 scale, any value outside this range was treated as invalid and corrected or removed when necessary. Missing data were examined at both the item and respondent levels. Cases with excessive missing responses were excluded, while minimal random missingness was handled through item-median imputation. Composite means were computed only when most items in a dimension were available. The data were also checked for low-quality response patterns, such as straight-lining, invariant responses, and duplicated answer sets, and clearly invalid cases were removed. Finally, all predictor variables were standardized into z-scores before PCA to ensure comparability and prevent variables with larger variance from dominating the component extraction.

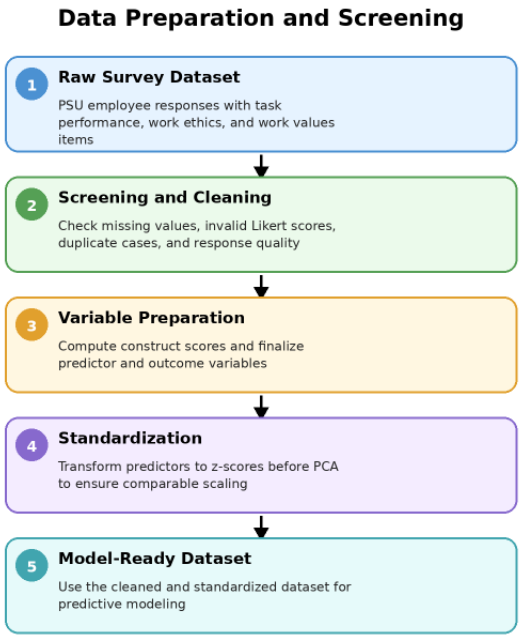

Fig. 1. Data preparation and screening.

F. Feature Engineering

Two parallel feature representations were used in the study: item-level predictors: all work ethics and work values items entered individually; and PCA-derived predictors: principal components extracted from the full predictor matrix.

The principal analysis used the PCA-derived feature space because the study proposes a hybrid PCA–Random Forest framework. The item-level representation was retained as a benchmark to determine whether PCA improved, reduced, or preserved predictive performance compared with a standard Random Forest using the original survey items.

G. Principal Component Analysis (PCA)

PCA was applied to the standardized predictor matrix composed of all work ethics and work values items. The purpose of PCA was to reduce redundancy among correlated survey items and derive a smaller number of orthogonal components that summarize the underlying variation in employees' ethics- and values-related responses. PCA is appropriate in multivariate measurement settings where many observed indicators capture overlapping constructs. Using multiple retention criteria is preferable because purely mechanical cutoffs may either retain noisy components or discard useful information. The retained principal components then served as the input features for the Random Forest model. This PCA stage helps reduce multicollinearity, compress noise, and improve model stability when many survey items are conceptually related.

The use of PCA before Random Forest was not based on the assumption that Random Forest requires uncorrelated predictors. Rather, PCA was used to address the high redundancy of the questionnaire indicators and to create a compact representation of the work ethics and work values domains. Since Random Forest can already handle correlated inputs, the hybrid model was evaluated against standard Random Forest to determine whether dimensionality reduction added practical value. This comparison is important because PCA may also introduce information loss when components do not preserve predictive patterns in the original variables.

H. Random Forest Regression

The predictive model used in the second stage was Random Forest Regression. Random Forest is an ensemble learning algorithm that builds multiple decision trees from bootstrap samples and aggregates their outputs to produce a final prediction. It is especially suitable for structured social science datasets because it can model nonlinear effects and variable interactions without requiring strict linearity or normality assumptions. The choice of Random Forest was justified because it handles moderate sample sizes effectively, it is robust to overfitting compared with single decision trees, it can capture nonlinear relationships between ethics, values, and performance, and it supports feature importance and post hoc interpretability analysis. Fig. 2 shows the model implementation process.

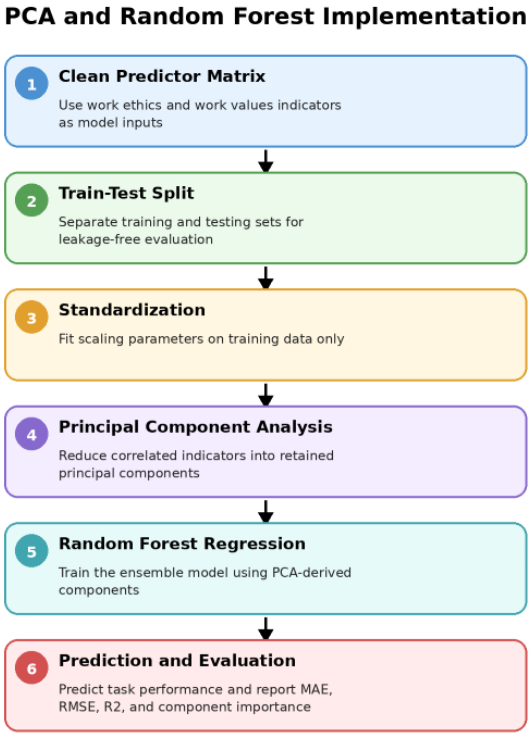

Fig. 2. PCA and random forest implementation.

I. Train–Test Procedure

To evaluate generalization performance, the dataset was partitioned into training and testing subsets. A practical split for the present sample is 80% training and 20% testing, with the random seed fixed for reproducibility. Model development, hyperparameter tuning, and PCA fitting were performed only on the training set to prevent information leakage. The trained transformation and model were then applied to the held-out test set. More specifically, the pipeline followed these steps:

- split the full dataset into training and testing sets,
- fit the standardization parameters using the training set only,

- fit PCA using the standardized training predictors only,
- transform both training and testing predictors using the fitted PCA model,
- train the Random Forest regressor on the transformed training set,
- generate predictions on the transformed test set.

This leakage-free workflow is aligned with best practices in supervised machine learning.

J. Hyperparameter Tuning

Random Forest performance depends on several tuning parameters. The following hyperparameters were optimized through k-fold cross-validation on the training set:

- number of trees (n_estimators),
- maximum tree depth (max_depth),
- minimum samples required to split a node (min_samples_split),
- minimum samples required at a leaf (min_samples_leaf),
- number of predictors considered at each split (max_features).

A 5-fold cross-validation procedure is suitable for the present sample size because it balances bias and variance in performance estimation. Grid search or randomized search may be used to identify the best-performing parameter combination. This is consistent with methodological recommendations for machine learning applications in psychology and social research.

K. Baseline and Comparative Models

To demonstrate the value of the hybrid approach, the PCA–Random Forest model should be compared against baseline models. The recommended comparison set includes:

- multiple linear regression,
- ridge regression or elastic net,
- decision tree regression,
- random forest without PCA.

Linear and regularized regression models provide interpretable baselines and are commonly recommended when working with many correlated predictors. Comparing the hybrid model against these alternatives allows the study to show whether PCA improves the predictive performance of Random Forest and whether nonlinear ensemble learning performs better than simpler linear approaches.

L. Model Evaluation Metrics

Model performance was evaluated using standard regression metrics. The principal metrics were Mean Absolute Error, Root Mean Squared Error, and Coefficient of Determination.

Robustness was examined by comparing cross-validation results with held-out test performance and by comparing the hybrid PCA–Random Forest model with standard Random Forest. Similar performance across cross-validation and test results was treated as evidence that the model was not merely fitting noise in one split of the data. Because the sample size was moderate, model complexity was controlled through cross-validation and hyperparameter tuning.

M. Model Interpretation

Because Random Forest is an ensemble model, interpretability must be explicitly addressed. The study, therefore, included a model explanation phase after prediction. Two levels of interpretation were proposed:

- Global interpretation, using permutation importance or impurity-based feature importance to determine which retained PCA components contributed most strongly to prediction,
- Local interpretation, using SHAP-based or Shapley-style explanation methods to estimate how features influenced individual predictions.

Interpretable machine learning is important because predictive accuracy alone is insufficient in applied organizational settings. Administrators need to know which dimensions of work ethics and work values are most strongly associated with employee performance in order to translate findings into policy or intervention. When PCA components are used, the interpretation should proceed in two stages: first, identify important components, then inspect the original variable loadings within those components to understand the substantive meaning of the prediction drivers.

For the hybrid model, interpretation was conducted by examining the importance of each retained principal component and then reviewing the original item loadings within the most influential components. Components were labelled based on the dominant work ethics and work values indicators that loaded on them. This procedure allowed the statistical output of PCA to be translated back into substantive organizational constructs.

N. Reliability and Measurement Assessment

Although the main contribution of the study is predictive, reliability and measurement adequacy should still be examined. For each major questionnaire dimension, Cronbach's alpha or an equivalent internal consistency statistic may be computed. This step helps establish that the grouped indicators used in the analysis show acceptable coherence. Psychometric evaluation remains important even in machine learning workflows because poor measurement quality can undermine predictive validity. In addition, descriptive statistics for each construct should be reported, including mean, standard deviation, minimum, maximum, skewness, and kurtosis. A correlation matrix may also be presented to show the extent of interdependence among the item groups before PCA.

O. Software Implementation

The analysis may be implemented in Python using standard scientific computing libraries:

- pandas for data handling,
- numpy for numerical operations,

- scikit-learn for standardization, PCA, train–test split, cross-validation, and Random Forest,
- matplotlib or seaborn for visual outputs,
- shap for model interpretation.

Python is appropriate because it supports end-to-end preprocessing, hybrid modeling, evaluation, and explainability within one reproducible workflow.

P. Ethical Considerations

The study used questionnaire responses from PSU employees and, therefore, involved human-subject data. Ethical handling of the dataset required that all records be analyzed in aggregate or anonymized form, with no direct personal identifiers retained in the modeling file. Access to the raw data should be limited to the researcher, and findings should be reported only at the level of patterns, not individual identities. These safeguards are especially important in workplace studies involving ethics, values, and performance.

III. Results and Discussions

This section presents the findings of the study and provides an interpretation of the results based on the data analysis. It highlights the patterns observed in the predictor constructs and compares the performance of the different regression models to explain their implications in relation to the objectives of the study.

A. Data Screening and Preliminary Analysis

The dataset contained 231 complete responses and 81 variables. No missing values were detected, and all item responses were within the valid Likert range of 1 to 5. This indicates that the dataset was already clean enough for predictive modeling without requiring imputation or deletion. A notable pattern in the data was the strong concentration of responses at the upper end of the scale. Across all item responses, about 69.8% were rated 5, 24.8% were rated 4, and only about 5.4% fell in the 1–3 range. This suggests that PSU employees generally rated themselves highly on work ethics, work values, and performance. At the same time, this pattern points to a likely ceiling effect, meaning the predictive models had to distinguish performance using relatively compressed high-score data rather than widely dispersed responses. The composite task performance score had a mean of 4.37 and a standard deviation of 0.50, with observed scores ranging from 2.86 to 5.00. This indicates that employee performance was generally high but still variable enough to support prediction.

The ceiling effect is an important limitation of the dataset. Since most responses were concentrated at the upper end of the scale, the models had less variation available for distinguishing respondents with different performance levels. This may reduce discrimination capability and may also explain why some normatively important constructs, such as integrity and transparency, were not among the strongest statistical predictors.

B. Reliability of the Scales

Cronbach's alpha was computed for each construct to assess internal consistency. All scales showed acceptable to excellent reliability. Table I shows the summary of the reliability test results.

TABLE I. Test of Reliability

Construct	Items	Mean	SD	Cronbach's alpha
Task performance	7	4.372	0.501	0.856
Commitment to public interest	7	4.417	0.506	0.743
Professionalism	7	4.552	0.428	0.843
Political neutrality	4	4.65	0.566	0.775
Justness and sincerity	5	4.764	0.413	0.901
Responsiveness to the public	6	4.689	0.399	0.862
Nationalism and patriotism	6	4.542	0.448	0.829
Commitment to democracy	3	4.641	0.531	0.922
Simple living	6	4.478	0.555	0.842
God-fearing	5	4.732	0.579	0.866
Accountability	5	4.718	0.439	0.9
Integrity	5	4.842	0.278	0.766
Transparency	5	4.808	0.347	0.852
Innovativeness	5	4.737	0.374	0.832
Competency	5	4.781	0.346	0.832

Table I reports reliability results for all major task performance, work ethics, and work values dimensions, including the number of items, mean, standard deviation, and Cronbach's alpha for each scale. This complete subscale reporting was added to allow readers to judge the internal consistency and measurement quality of every dimension included in the predictive model.

These findings show that the questionnaire dimensions were sufficiently coherent for both descriptive analysis and machine-learning modeling. The strongest reliability estimates were found for commitment to democracy ($\alpha = 0.922$), justness and sincerity ($\alpha = 0.901$), and accountability ($\alpha = 0.900$), while the lowest, though still acceptable, was commitment to public interest ($\alpha = 0.743$).

C. Descriptive Results

Among the predictor constructs, the highest mean scores were recorded for integrity (4.842), followed by transparency (4.808), competency (4.781), justness and sincerity (4.764), and innovativeness (4.737). In contrast, the lowest mean scores, although still relatively high, were found in task performance (4.372), commitment to public interest (4.417), simple living (4.478), nationalism and patriotism (4.542), and professionalism (4.552). This pattern suggests that PSU employees rated themselves most strongly in terms of personal and ethical standards, particularly integrity, transparency, and competency, while somewhat lower ratings were observed in more behaviorally demanding or institutionally oriented dimensions such as task performance and commitment to public interest. Substantively, this may indicate that respondents viewed themselves as highly principled and capable, but less uniformly

strong in consistently translating these values and orientations into high task-performance outcomes. Since all mean scores are well above 4.0, the issue does not appear to be weak ethics or poor performance, but rather which dimensions are most effective in explaining differences among an already high-performing group of respondents.

D. Bivariate Relationship with Task Performance

Table II shows the strongest positive correlations with task performance.

TABLE II. SUMMARY OF CORRELATION

Predictor construct	Correlation with task performance
Professionalism	0.455
Commitment to public interest	0.418
Nationalism and patriotism	0.36
Justness and sincerity	0.346
Responsiveness to the public	0.334
Accountability	0.314
Political neutrality	0.313
Commitment to democracy	0.305
Simple living	0.265
Integrity	0.241

These results suggest that professionalism had the strongest linear association with employee performance, followed by commitment to public interest. This is intuitive because the task-performance indicators focus on planning, efficiency, quality, and work execution, which are behaviorally close to professional conduct and duty orientation.

The weaker, though still positive, association of integrity with performance is also meaningful. Integrity had the highest descriptive mean, which implies little variation between respondents. When most respondents rate integrity very highly, it contributes less to differentiating who performs better than others. In short, a construct can be important normatively without being the strongest statistical predictor if almost everyone scores high on it.

The findings show that the hybrid PCA–Random Forest model did not substantially outperform the standard Random Forest model. The standard Random Forest achieved a slightly higher held-out R^2, whereas the hybrid model achieved a slightly lower MAE and comparable RMSE. Therefore, the main contribution of the hybrid model is not a large gain in predictive accuracy, but the ability to reduce 74 predictor items to 19 components while preserving almost the same level of predictive performance. This makes the model more compact and less redundant, which is useful for interpretation and future implementation.

E. Predictive Model Performance

Six regression models were estimated and compared using the uploaded item-level predictors: Linear Regression, Ridge Regression, Elastic Net, Decision Tree, Random Forest, and a Hybrid PCA–Random Forest model. The hybrid approach first applied principal component analysis (PCA) to reduce the 74 predictor items into 19 principal components, which together accounted for 80.9% of the variance in the predictor space. These extracted components were then used as inputs to a Random Forest regressor.

TABLE III. CROSS-VALIDATION TEST RESULTS

Model	CV MAE	CV RMSE	CV R^2
Linear Regression	0.378	0.536	0.119
Ridge Regression	0.365	0.512	0.213
Elastic Net	0.36	0.453	0.38
Decision Tree	0.328	0.43	0.417
Random Forest	0.272	0.378	0.526
PCA–Random Forest	0.272	0.376	0.524

TABLE IV. HELD-OUT TEST RESULTS

Model	Test MAE	Test RMSE	Test R^2
Linear Regression	0.385	0.522	0.119
Ridge Regression	0.365	0.493	0.213
Elastic Net	0.357	0.438	0.38
Decision Tree	0.301	0.424	0.417
Random Forest	0.283	0.383	0.526
PCA–Random Forest	0.272	0.383	0.524

Table III and IV show the test results of cross-validation and held-out. The main result is that the ensemble models clearly outperformed the linear models. Both Random Forest and PCA–Random Forest substantially improved prediction relative to Linear Regression, Ridge, and Elastic Net. This means the relationship between employee performance and the ethics-values predictors is not purely linear. Instead, the data appear to contain interaction effects, nonlinearities, or threshold-like patterns, which tree-based ensemble methods are better able to capture.

The best overall performance was shared by the two Random Forest variants. The standard Random Forest had the best test RMSE (0.383) and test R^2 (0.526), while the PCA–Random Forest had the best test MAE (0.272) and the best cross-validated RMSE (0.376). In practical terms, the difference between the two is very small. The implication for the study:

- if emphasis is pure predictive accuracy, the standard Random Forest is marginally stronger,
- if emphasis is on the hybrid framework named in the title, then the PCA–Random Forest is fully defensible because it performed essentially the same while reducing the predictor space from 74 items to 19 components.

That is a strong methodological result. It means that PCA compressed the survey into a more manageable representation without materially sacrificing predictive power.

F. Why the Hybrid PCA–Random Forest Model Worked

The hybrid model worked well for two reasons. First, the survey contains many conceptually related Likert items. For example, professionalism, accountability, transparency, and

competency are distinct constructs but are likely to co-vary in practice. PCA helped summarize these overlapping responses into a smaller number of orthogonal dimensions, reducing redundancy and multicollinearity. Second, Random Forest was able to model the resulting component space flexibly. Because employee behavior is rarely determined by one variable in a simple linear way, the ensemble model likely captured combinations such as:

- strong professionalism plus strong public responsiveness,
- high public-interest orientation plus accountability,
- or moderate scores across several ethical domains rather than a single dominant trait.

This is exactly the kind of pattern that Random Forest handles better than ordinary linear regression.

G. Feature Importance and Substantive Predictors

Table V shows the feature importance and substantive predictors. The most important predictor was professionalism, which is consistent with the correlation results. This suggests that employees who reported stronger adherence to professional conduct also tended to have higher task-performance scores. This makes theoretical sense because professionalism reflects disciplined work behavior, standard procedure compliance, and appropriate workplace conduct, which are closely aligned with task execution.

TABLE V. FEATURE IMPORTANCE AND SUBSTANTIVE PREDICTORS

Construct	Importance
Professionalism	0.203
Nationalism and patriotism	0.117
Commitment to public interest	0.077
Simple living	0.064
Political neutrality	0.057
God-fearing	0.055
Innovativeness	0.043
Responsiveness to the public	0.034
Justness and sincerity	0.027
Accountability	0.026

The second strongest predictor was nationalism and patriotism, which is interesting because it was not the highest-mean construct. This suggests that while patriotism-related items may not be the most highly endorsed overall, they contributed meaningful variation in performance prediction. In the PSU setting, this may reflect a broader sense of institutional duty, public commitment, and mission alignment.

Commitment to public interest also emerged as a key predictor. This is important because it directly reflects service orientation and responsible use of public resources, both of which are highly relevant to employee effectiveness in a public institution.

A particularly interesting result is that integrity, despite having the highest mean score, was not among the strongest predictive variables. This likely reflects restricted variance: when almost everyone scores high on integrity, it cannot separate higher-performing from lower-performing employees as strongly as more behaviorally variable constructs such as professionalism.

H. PCA Structure of the Hybrid Model

The PCA stage retained 19 components explaining 80.9% of the total predictor variance. The first principal component alone explained about 25.5% of the variance, suggesting a strong common dimension underlying many of the ethics and values items.

The most influential component in the hybrid model was PC1, far more important than the remaining components. Its strongest loadings came from items related to:

- justness and sincerity,
- commitment to democracy,
- professionalism,
- transparency,
- nationalism/patriotism,
- and simple living.

This suggests that the first component captured a broad ethical-public service orientation, and that this general orientation played a major role in predicting employee performance.

Based on the dominant loadings, PC1 was interpreted as a Broad Ethical-Public Service Orientation component because it combined justness and sincerity, commitment to democracy, professionalism, transparency, nationalism and patriotism, and simple living. This label indicates that the strongest component represented a general pattern of ethical conduct, public accountability, and disciplined professional behavior.

From a discussion standpoint, this means that performance in PSU may not depend on isolated moral traits alone, but on a clustered ethical profile combining fairness, professionalism, service orientation, and responsibility. In other words, the model points to a multidimensional moral-professional foundation for effective task performance.

I. Discussion of the Result

The overall descriptive results show a strongly positive self-assessment pattern. This may reflect genuinely high organizational standards, but it may also indicate socially desirable responding, especially in self-report ethics measures. Because the survey asks respondents to rate highly valued public-service behaviors, upward skew is not surprising.

The reliance on self-reported survey data may have inflated the observed scores because employees may respond in ways that reflect socially desirable behavior. This is especially likely for ethics and values indicators. Future studies should triangulate self-report measures with supervisor ratings, peer

assessments, attendance records, productivity indicators, or other administrative performance data.

Even so, the variation that remained was enough for machine learning to explain about 52% of the performance variance. That is substantial for social-science survey data and suggests that work ethics and work values contain meaningful predictive information.

Across both correlation and feature-importance analyses, professionalism emerged as the dominant predictor. This is a strong and coherent result. It implies that among the many moral and value-based dimensions in the questionnaire, the construct most directly tied to actual performance is the one most closely linked to work discipline, standards, competence in role behavior, and execution of duty.

This finding is particularly useful for institutional practice because professionalism is also one of the most actionable domains. It can be strengthened through training, supervision, performance feedback, and policy reinforcement.

The data do not suggest that ethics and values are irrelevant; quite the opposite. However, they indicate that some domains matter more for performance differentiation than others. Broadly endorsed traits such as integrity and transparency may represent foundational norms, but they did not distinguish performance as strongly as professionalism, public-interest orientation, and nationalism/patriotism.

This distinction is important. It suggests that normative importance and predictive importance are not the same thing. A value may be central to institutional identity but still show weaker statistical prediction if it varies little across respondents.

The consistent superiority of Random Forest over Linear Regression, Ridge, and Elastic Net shows that this type of survey data benefits from nonlinear modeling. In practical terms, employee performance appears to arise from combinations of values rather than from simple additive effects.

A very important discussion point is that the hybrid model did not massively outperform standard Random Forest. But it also did not lose meaningful accuracy, despite reducing 74 predictors to 19 components.

That is still a success. It means the hybrid approach offers:

- dimensionality reduction,
- less redundancy,
- easier modeling,
- and nearly identical predictive performance.

So, in the study, the correct interpretation is not that PCA made Random Forest vastly more accurate, but that it made the model more compact and methodologically elegant without sacrificing accuracy.

This result also suggests that PCA should be viewed as a feature-compression strategy rather than as an automatic accuracy-improvement technique. Because Random Forest can internally manage correlated predictors, PCA is most useful here for reducing dimensionality and summarizing overlapping questionnaire items. The near-equivalent performance of both models indicates that the compressed component structure retained most of the useful predictive information from the original survey items.

J. Implications of the Findings

The results suggest that PSU can improve employee performance by focusing on the ethics and values dimensions that show the strongest predictive contribution, especially:

- professionalism,
- commitment to public interest,
- nationalism and patriotism,
- and selected value-based domains tied to accountability and service.

For organizational development, this means that ethics programs should not remain purely abstract or compliance-based. They should be linked to concrete performance behaviors such as planning work, delivering outputs on time, and maintaining high-quality service.

The findings also support the use of machine learning in HR and organizational research within educational institutions. A hybrid PCA–Random Forest framework can help identify which ethical and value-based dimensions are most useful in explaining performance variation, especially when many survey items overlap conceptually.

For practical deployment, the model should be used as a decision-support tool rather than as a punitive or fully automated evaluation system. Predictions should be reviewed in aggregate, anonymized where possible, and combined with professional judgment and existing human resource procedures. The model should also be monitored for stability over time and revalidated before being applied to other campuses, institutions, or employee groups.

IV. Conclusion and Recommendations

This section summarizes the major findings of the study and draws overall conclusions and future work based on the results obtained. It synthesizes the key insights from the analysis and emphasizes their significance in addressing the research objectives.

A. Conclusion

This study developed and evaluated a hybrid PCA–Random Forest model to predict employee performance from work ethics and work values among PSU employees. Results showed generally high levels of task performance, work ethics, and work values, indicating strong adherence to ethical standards and positive work-related values. Despite these high ratings, sufficient variation in task performance remained to support predictive modeling and model comparison.

Reliability analysis showed that the questionnaire dimensions had acceptable to excellent internal consistency, confirming the instrument's suitability for both descriptive and predictive analysis. In model evaluation, ensemble-based methods outperformed traditional linear approaches. Random Forest and the hybrid PCA–Random Forest model achieved the best predictive performance, suggesting that employee

performance is shaped by nonlinear and interaction-based relationships among work ethics and work values. Although the standard Random Forest yielded slightly better results on some metrics, the hybrid model remained highly competitive while reducing the predictor space to a smaller set of principal components.

Among the predictors, professionalism emerged as the strongest determinant of employee performance, followed by commitment to public interest, nationalism, and patriotism. These findings indicate that employee performance at PSU is more strongly associated with ethical-professional orientations related to discipline, accountability, and public service. Overall, the results support the hybrid PCA–Random Forest model as a valid and practical approach for predicting employee performance in a public university context and demonstrate the value of machine learning in examining ethics- and values-based factors in the workplace.

B. Recommendations

Based on the findings, PSU should strengthen programs that promote professionalism, since it emerged as the strongest predictor of task performance. The university should also continue reinforcing its commitment to public interest and other service-oriented values through training and development activities.

In addition, ethics and values-based interventions should be integrated more directly into performance improvement programs. PSU may also use data-driven tools, such as Random Forest and hybrid PCA–Random Forest models, to support employee assessment and human resource decisions.

For future research, the model should be tested using larger and more diverse samples from other universities, government agencies, or private organizations. External validation is necessary to determine whether the predictive patterns observed in the PSU dataset generalize to other organizational and cultural contexts. Future studies should also use longitudinal designs to examine possible causal pathways, combine self-reported data with supervisor or administrative performance records, conduct robustness and sensitivity analyses across repeated splits or bootstrapped samples, and provide full PCA loading tables and complete correlation matrices for transparency.

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