Perbanas International Conference on Economics, Business, Management, Accounting and IT (PROFICIENT) 2026
"Integrity-Driven Innovation: Reimagining Business, Finance, and Digital Transformation for Sustainable Impact"

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

The Influence of Knowledge Acquisition and Knowledge Application on Employee Performance and Retention in Digital Organizations

Chelsea Aulia Zahra[1], Ines Kartika Dewi[2,], Andika[3,], Alrafiful Rahman[4)]

[1,2,3,4] *Data Science Study Program, Faculty of Information Technology, Perbanas Institute*

[a)]Corresponding author : chelsea.aulia03@perbanas.id
[b)] ines.kartika05@perbanas.id
[c)] andika.04@perbanas.id
[d)] alrafiful.rahman@perbanas.id

Abstract. *This study examines the influence of knowledge acquisition and knowledge application on employee performance and retention in digital organizations. In the era of rapid technological advancement, organizations increasingly rely on effective knowledge management practices to remain competitive. Knowledge acquisition refers to the process of obtaining relevant information, skills, and insights, while knowledge application involves the effective use of that knowledge in daily tasks and decision-making. This research aims to analyze how these two factors contribute to improving employee performance and enhancing retention rates.A quantitative research approach was employed using survey data collected from employees working in digital-based organizations. Statistical analysis was conducted to evaluate the relationships between knowledge acquisition, knowledge application, employee performance, and retention. The findings indicate that both knowledge acquisition and knowledge application have a significant positive impact on employee performance. Furthermore, the effective application of knowledge plays a crucial role in increasing employee retention by fostering job satisfaction and organizational commitment.The results suggest that organizations should invest in continuous learning opportunities and create environments that encourage knowledge sharing and practical implementation. By strengthening knowledge management practices, digital organizations can improve overall performance and reduce employee turnover, ensuring long-term sustainability and competitiveness.*

Keywords: Knowledge Acquisition, Knowledge Application, Employee Performance, Employee Retention, Digital Organizations

INTRODUCTION

In the era of rapid digital transformation, organizations are increasingly dependent on knowledge as a critical asset to maintain competitiveness and sustainability. Digital organizations operate in highly dynamic environments where continuous learning, innovation, and adaptation are essential. As a result, effective knowledge management practices have become a key factor in enhancing organizational performance and ensuring long-term success (Nonaka, 2009). Among these practices, knowledge acquisition and knowledge application play a crucial role in shaping how employees contribute to organizational goals. Knowledge acquisition refers to the process through which individuals and organizations obtain new information, skills, and insights from both internal and external sources (Gold et al., 2001). Meanwhile, knowledge application involves the effective use of acquired knowledge in performing tasks, solving problems, and making decisions. When employees are able not only to acquire but also to apply knowledge effectively, they are more likely to perform better and adapt to changing work demands (Alavi & Leidner, 2001). This, in turn, can influence their level of job satisfaction and commitment to the organization.

Employee performance and retention are two important indicators of organizational success, especially in digital environments where competition for skilled talent is high. Organizations that fail to manage knowledge effectively may experience decreased productivity and higher turnover rates (Davenport & Prusak, 1998). Therefore, understanding the relationship between knowledge acquisition, knowledge application, employee performance, and retention is essential. This study aims to examine the influence of knowledge acquisition and knowledge application on employee performance and retention in digital organizations, providing insights into how knowledge management practices can support organizational effectiveness.

LITERATURE REVIEW

Knowledge Management

Knowledge management is a systematic process of creating, acquiring, sharing, and applying knowledge within an organization to enhance performance and achieve strategic goals. In digital organizations, knowledge management plays a crucial role in supporting innovation, efficiency, and competitiveness. Organizations that effectively manage knowledge resources are better positioned to respond to rapid technological changes and dynamic market conditions (Nonaka, 2009).

Knowledge Acquisition

Knowledge acquisition refers to the process of obtaining knowledge from various sources, both internal and external. This includes learning through training, experience, collaboration, and access to information systems. Effective knowledge acquisition enables employees to continuously develop their skills and competencies, which is essential in digital environments that require adaptability and continuous learning (Gold et al., 2001).

Knowledge Acquisition

Knowledge application is the process of utilizing acquired knowledge in practical situations, such as completing tasks, solving problems, and making decisions. It is a critical stage in knowledge management because it transforms knowledge into tangible outcomes. Employees who are able to effectively apply knowledge tend to demonstrate higher productivity, creativity, and problem-solving abilities (Alavi & Leidner, 2001).

Employee Performance

Employee performance refers to the level of achievement of tasks and responsibilities assigned to individuals within an organization. It is influenced by various factors, including skills, motivation, and access to relevant knowledge. High levels of knowledge acquisition and application contribute positively to employee performance by enabling individuals to work more efficiently and effectively in achieving organizational objectives (Alavi & Leidner, 2001).

Employee Retention

Employee retention is the organization's ability to retain its employees over time. In digital organizations, retaining skilled employees is a major challenge due to high competition in the labor market. Effective knowledge management practices, particularly knowledge acquisition and application, can increase job satisfaction, organizational commitment, and ultimately reduce employee turnover (Davenport & Prusak, 1998).

Relationship Between Variables

Previous studies indicate that knowledge acquisition and knowledge application have a significant impact on employee performance and retention. Knowledge acquisition enhances employees' capabilities, while knowledge application ensures that these capabilities are effectively utilized. Together, they contribute to

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

improved performance and increased retention, making them critical factors in the success of digital organizations (Nonaka, 2009) (Gold et al., 2001) (Alavi & Leidner, 2001) (Davenport & Prusak, 1998).

METHODS

Research Design

This study uses a quantitative research approach to analyze the influence of knowledge acquisition and knowledge application on employee performance and retention in digital organizations. The research also applies machine learning techniques using the Random Forest algorithm to identify patterns and relationships between variables. Quantitative methods are considered effective for analyzing numerical data and testing relationships among variables systematically (Creswell & Creswell, 2017).

Data Source

The dataset used in this study was obtained from a public dataset related to employee development and organizational performance. The dataset contains information regarding employee training, work experience, educational background, and other factors associated with knowledge management practices.

Data Preprocessing

Several preprocessing techniques were applied before building the model. Missing values in numerical data were replaced using median values, while categorical data were filled using mode values. Furthermore, categorical variables were transformed into numerical form using Label Encoding to support machine learning analysis (Géron, 2022).

Feature Selection

The independent variables in this study include factors related to knowledge acquisition and knowledge application, while the dependent variables focus on employee performance and retention indicators. Feature selection was conducted to identify the most relevant variables affecting the prediction results.

Data Splitting

The dataset was divided into training data and testing data using the train-test split method. Approximately 80% of the data was used for training and 20% for testing to evaluate model performance objectively (Hastie et al., 2009).

Random Forest Model

The Random Forest Classifier algorithm was implemented in this study because of its effectiveness in classification tasks and its ability to handle complex datasets with high accuracy. Random Forest combines multiple decision trees to improve prediction performance and reduce overfitting problems (Breiman et al., 1984).

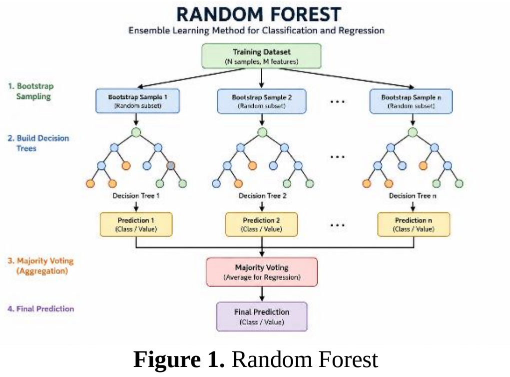

Figure 1. Random Forest

The figure illustrates the working process of the Random Forest algorithm, which is an ensemble learning method used for classification and regression tasks (Breiman, 2001). The process begins with the training

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

dataset, where multiple bootstrap samples are created through random sampling. Each sample is then used to build separate decision trees.
After all decision trees generate predictions, the Random Forest algorithm combines the results using a majority voting method for classification or averaging for regression. The final prediction is determined based on the combined outputs from all trees. This approach helps improve prediction accuracy and reduce overfitting compared to a single decision tree (Géron, 2022).

Model Evaluation
The model performance was evaluated using several metrics, including accuracy score, precision, recall, F1-score, confusion matrix, and ROC curve analysis. These evaluation techniques were used to measure the effectiveness and reliability of the classification model (Hao & Ho, 2019).

Data Visualization
Visualization techniques such as confusion matrix heatmaps and feature importance charts were used to present the analysis results clearly and improve interpretation of the findings.

RESULTS AND DISCUSSION

Model Evaluation

The evaluation process in this study was conducted using several performance metrics, namely accuracy, precision, recall, and F1-score. These metrics were calculated based on the confusion matrix to determine the effectiveness of the Random Forest classification model.

Confusion Matrix

Actual Class	Predicted Positive	Predicted Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

Tabel 1. Confusion Matrix

Confusion Matrix Analysis

The figure above presents the Confusion Matrix generated from the Random Forest classification model. A confusion matrix is used to evaluate the performance of a classification model by comparing actual values with predicted values (Hao & Ho, 2019).

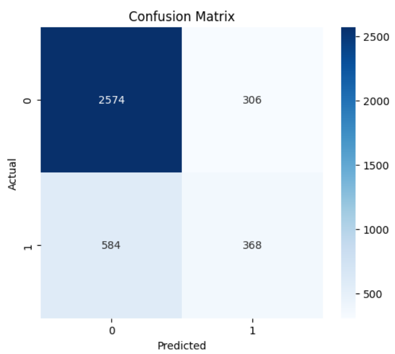

Figure 2. Confusion Matrix

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

The matrix shows that:

- 2574 data instances were correctly classified as class 0 (True Negative).
- 368 data instances were correctly classified as class 1 (True Positive).
- 306 data instances were incorrectly predicted as class 1 when the actual class was 0 (False Positive).
- 584 data instances were incorrectly predicted as class 0 when the actual class was 1 (False Negative).

The results indicate that the model performs better in predicting class 0 compared to class 1. The relatively high number of false negatives suggests that the model still has difficulty identifying some positive cases correctly. However, overall, the confusion matrix demonstrates that the Random Forest model achieved good classification performance.

Accuracy

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Accuracy measures the proportion of correctly classified instances among all predictions. In this study, the Random Forest model achieved an accuracy score of **0.7677 (76.77%)**, indicating a reasonably good overall classification performance. However, accuracy alone may be misleading in imbalanced datasets, as it can be dominated by the majority class (Hao & Ho, 2019).

Precision

$$Precision = \frac{TP}{TP + FP}$$

Precision indicates how many of the predicted positive instances are actually correct. For class 0.0, the precision is **0.82**, while for class 1.0 it is **0.55**. This shows that the model performs better in correctly predicting class 0 compared to class 1 (Powers, 2020).

Recall

$$Recall = \frac{TP}{TP + FN}$$

Recall measures the model's ability to identify all actual positive instances. The recall for class 0.0 is **0.89**, while for class 1.0 it drops to **0.39**, indicating that the model struggles to correctly detect class 1, which may represent the minority class (Sokolova & Lapalme, 2009; Powers, 2020).

F1-Score

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The F1-score represents the harmonic mean of precision and recall, providing a balance between the two metrics. The F1-score for class 0.0 is **0.85**, while for class 1.0 it is **0.45**, indicating strong performance on class 0 but weaker performance on class 1 (Powers, 2020).

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

Classification Report

Class	Precision	Recall	F1-Score	Support
0.0	0.82	0.89	0.85	2880
1.0	0.55	0.39	0.45	952

Tabel 2. Classification Report

Metric	Value
Accuracy	7.677
Macro Average F1-Score	0.65
Weighted Average F1-Score	0.75

Tabel 3. Classification Report

Classification Result Range

Metric	Value	Interpretation
Accuracy	7.677	Good classification performance
Precision (Class 0.0)	0.82	High prediction precision
Precision (Class 1.0)	0.55	Moderate prediction precision
Recall (Class 0.0)	0.89	Very good detection capability
Recall (Class 1.0)	0.39	Low detection capability
F1-Score (Class 0.0)	0.85	Strong model balance
F1-Score (Class 1.0)	0.45	Moderate model balance

Tabel 4. Classification Result Range

The evaluation results indicate that the Random Forest algorithm performs effectively in predicting employee performance and retention. However, the lower recall value for class 1.0 suggests that further model optimization may still be required. The performance of the Random Forest model was evaluated using several classification metrics, including accuracy, precision, recall, and F1-score (Breiman, 2001).

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

Feature Importance Analysis

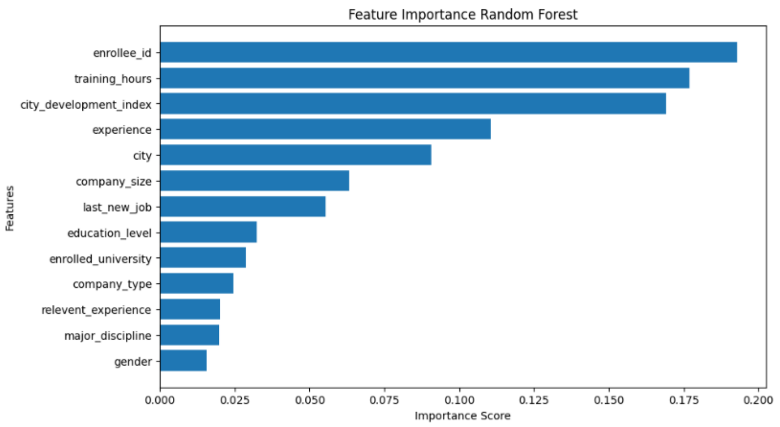

Figure 3. Feature Importance Analysis

The figure above shows the feature importance results generated using the Random Forest algorithm. Feature importance is used to identify which variables have the greatest influence on the prediction model (Breiman, 2001).

Based on the chart, **enrollee_id**, **training_hours**, and **city_development_index** have the highest importance scores, indicating that these variables contribute the most to predicting employee performance and retention. In contrast, variables such as **gender**, **major_discipline**, and **relevent_experience** show lower importance scores, meaning they have less influence on the model predictions.

The results indicate that training activities, work experience, and organizational development factors play an important role in supporting employee performance and retention in digital organizations.

CONCLUSIONS

This study concludes that knowledge acquisition and knowledge application significantly influence employee performance and retention in digital organizations. Employees who continuously acquire and apply knowledge effectively tend to demonstrate better productivity, adaptability, and organizational commitment.

The implementation of the Random Forest algorithm also proved effective in analyzing employee-related outcomes, achieving an accuracy score of 76.77%. The findings highlight the importance of effective knowledge management practices in improving organizational sustainability and reducing employee turnover.

Organizations are encouraged to invest in continuous learning programs, training activities, and knowledge-sharing environments to strengthen employee performance and retention in the digital era.

Acknowledgments

The authors would like to thank the lecturers of the Project Management and Data Analytics course in the Data Science Study Program at the Faculty of Information Technology, Perbanas Institute Jakarta, for providing the opportunity to conduct and present this research at the Perbanas International Conference (PROFICIENT) 2026.

References

Alavi, M., & Leidner, D. E. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues1, 2. *MIS Quarterly*, *25*(1), 107–136.

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Breiman, L., Friedman, J., Stone, C., & Olshen, R. (1984). *Classification and regression trees (crc, boca raton, fl)*.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Davenport, T. H., & Prusak, L. (1998). *Working knowledge: How organizations manage what they know*. Harvard Business Press.

Géron, A. (2022). *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow*. " O'Reilly Media, Inc."

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. *Journal of Management Information Systems*, *18*(1), 185–214.

Hao, J., & Ho, T. K. (2019). Machine learning made easy: a review of scikit-learn package in python programming language. *Journal of Educational and Behavioral Statistics*, *44*(3), 348–361.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning*. Springer series in statistics New-York.

Nonaka, I. (2009). The knowledge-creating company. In *The economic impact of knowledge* (pp. 175–187). Routledge.

Powers, D. M. W. (2020). Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. *ArXiv Preprint ArXiv:2010.16061*.

Sokolova, M., & Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Information Processing & Management*, *45*(4), 427–437.