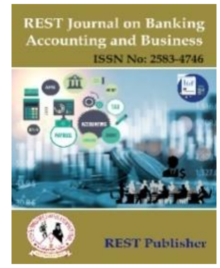
REST Journal on Banking, Accounting and Business

Vol: 4(4), December 2025

REST Publisher; ISSN: 2583 4746

Website: http://restpublisher.com/journals/jbab/

DOI: https://doi.org/10.46632/jbab/4/4/8



Exploring the Impact of Knowledge Management Dimensions on Organizational Performance: A Machine Learning Approach

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Abstract: *Knowledge management represents a critical organizational capability for capturing, sharing, and leveraging collective knowledge to achieve strategic objectives in today's competitive business environment. This research examines how the four essential aspects of knowledge management – sharing, creating, storing and using knowledge – are interrelated and affect the effectiveness of overall knowledge management. Survey data from 30 organizational respondents were analyzed using descriptive statistics, correlation analysis, and two predictive modeling approaches: linear regression and slope-increasing regression. The findings demonstrate strong positive correlations between all knowledge management practices and how well organizations perform, with correlation values between 0.85 and 0.96. Knowledge sharing showed the most powerful correlation with performance at 0.96, while knowledge application came in second at 0.92. Both prediction models performed remarkably well – the linear regression model explained 98.27% of the variance in the experimental data with an R^2 of 0.9827, and the slope-increasing regression model achieved 0.9283, showing that these four dimensions' account for more than 92% of the variance in knowledge management performance. The findings suggest that balanced implementation across all knowledge management practices yields better organizational outcomes, with knowledge creation and knowledge use emerging as influential drivers of success. This research provides empirical evidence supporting integrated knowledge management strategies and offers practical insights for organizations looking to improve their knowledge management capabilities.*

Key words: *Knowledge management, knowledge sharing, knowledge creation, linear regression, slope-increasing regression, organizational performance, machine learning.*

1. INTRODUCTION

Knowledge management involves the organized management of how organizations create, distribute, use, and monitor their knowledge and information resources. It encompasses a multifaceted strategy for achieving organizational goals by optimizing knowledge utilization. In today's rapidly evolving business landscape characterized by information overload and fierce competition, successful knowledge management has emerged as a key component for sustaining competitiveness and fostering innovation [1]. Essentially, knowledge management involves the collection of two types of knowledge: explicit knowledge, which consists of readily available information recorded in databases, manuals, and reports, and tacit knowledge, which resides in the minds of individuals and is derived from experience, insight, and intuition [2]. The main challenge lies in transforming tacit knowledge into explicit forms so that it can be shared across the organization. This process ensures that valuable expertise is not lost when employees leave and that best practices continue to be used throughout the organization. Implementing knowledge management systems typically involves several key components. First, there must be a robust technology infrastructure that facilitates the storage, retrieval, and dissemination of information [3]. This includes intranets, content management systems, collaborative platforms, and artificial intelligence tools that help organize and surface relevant information. However, technology alone is not enough. Organizations must also foster a culture that values knowledge sharing and collaboration [4]. This cultural dimension is often the most challenging aspect, as it requires overcoming territorial behaviors and encouraging employees to View knowledge as a shared organizational resource, not as a personal tool for gaining power.

Knowledge management processes typically follow a life cycle that includes knowledge creation, storage, sharing, and use [5]. Creation involves generating new insights through research, experimentation, and learning from both successes and setbacks. Storage involves structuring this knowledge in accessible databases with appropriate metadata and search functions. Sharing involves distributing knowledge through formal means such as training programs and documents, and informal means such as communities of practice and mentoring partnerships [6]. Ultimately, application ensures that knowledge is actively used in decision-making and problem-solving situations, completing the cycle and frequently creating new knowledge along the way. The benefits of successful knowledge management are significant and diverse. Organizations can significantly reduce unnecessary work by preventing employees from accidentally repeating tasks or reinventing existing solutions [7]." Decision-making improves when relevant historical information and expert expertise are easily accessible. Innovation accelerates as individuals can leverage existing knowledge instead of starting from scratch. Customer service improves when support staff can instantly retrieve detailed product details and answers to frequently encountered problems [8]. Employee recruitment is further streamlined when organizational knowledge is fully documented and readily available, reducing the time it takes for new employees to reach full productivity. However, knowledge management efforts face several common obstacles. A significant obstacle is reluctance to embrace change, as employees may be reluctant to change familiar work processes or contribute knowledge that they perceive as protecting their job security [9]. Information overload poses another challenge, as too much disorganized data can be just as disruptive as too little. Organizations need to establish robust filtering, classification, and search systems to help people find the most relevant content. Furthermore, maintaining the accuracy of knowledge requires ongoing effort and investment, as outdated information is more harmful than none at all [10]. Leadership plays a key role in effective knowledge management. Top executives must support these efforts, dedicate adequate resources, and demonstrate knowledge sharing practices themselves. They must create well-defined governance structures that specify roles, accountabilities, and procedures for overseeing organizational knowledge [11]. This includes creating reward mechanisms that encourage knowledge sharing and setting performance indicators to assess knowledge management effectiveness. Moving forward, knowledge management will continue to advance with technological advancements [12]. Artificial intelligence and machine learning are increasingly being used to streamline knowledge capture, improve search and retrieval processes, and extract insights from vast datasets. Social and collaborative technologies are making knowledge sharing more natural and embedded in everyday workflows [13]. As remote and hybrid work models become more widespread, effective knowledge management becomes even more critical to maintaining organizational cohesion and ensuring that distributed teams have access to the information they need [14]. Ultimately, successful knowledge management is not just about implementing systems and processes – it's about creating an environment where learning is continuous, knowledge flows freely, and collective intelligence drives organizational success. Organizations that excel at knowledge management position themselves to adapt quickly to change, innovate more effectively, and leverage the collective knowledge of their people [15].

2. METHODOLOGY

Linear regression: Linear regression is a basic statistical technique used to describe the relationship between a dependent variable and one or more dependent variables. It assumes a linear relationship, which implies that changes in the dependent variable(s) cause proportional changes in the dependent variable. This method works by fitting a straight line through the data points, which minimizes the total squared differences between the actual and predicted values. In simple linear regression, one independent variable predicts an outcome, whereas multiple linear regression uses multiple predictors. This approach is widely used in fields such as economics, finance, and data science to predict, analyze trends, and understand how variables interact. Linear regression yields explanatory coefficients that measure the influence of each variable on the outcome.

Gradient Boosting Regression: Gradient boosting is a sophisticated machine learning method that builds predictive models by combining multiple weak learners, typically decision trees, through an iterative process. In contrast to conventional approaches, it builds each subsequent tree to correct errors from previous trees, focusing on residuals or prediction inaccuracies. This iterative process gradually improves accuracy by introducing models that address persistent errors. This algorithm uses gradient boosting to minimize the loss function, which explains the "slope" in its name. It has proven to be very effective for complex datasets and often outperforms simpler techniques in predictive accuracy. Gradient boosting is gaining widespread use in competitions and practical applications across finance, healthcare, and recommendation systems, although careful parameter tuning is necessary to avoid overfitting.

In put: Knowledge sharing involves the dissemination of information and expertise throughout an organization, both through formal channels such as training programs and documents, and through informal methods such as mentoring and collaborative platforms. Effective sharing breaks down barriers, encourages collaboration, and ensures that valuable insights reach those who need them for improved decision-making and innovation. Knowledge creation is the process of generating new insights, ideas, and expertise through research, experimentation, problem-solving skills, and learning from experiences. Organizations foster creativity by encouraging innovation, supporting continuous learning, providing resources for exploration, and drawing lessons from both successes and failures to expand their collective intelligence. Knowledge storage involves organizing and preserving information in accessible repositories using databases, content management systems, and documentation platforms. To ensure that knowledge is retrievable and useful, effective storage requires proper classification, metadata tagging, and search capabilities. Regular updates and maintenance prevent information from becoming outdated or lost over time. Knowledge application involves the use of stored knowledge for decision-making, problem-solving, and innovation purposes. This critical step converts information into actionable value, closing the knowledge management loop. Successful application requires making knowledge accessible when needed and creating cultures where employees actively use available expertise rather than relying solely on personal experience.

Output: Knowledge management performance measures how well an organization captures, shares, and uses its collective knowledge to achieve strategic objectives. It is assessed through metrics such as employee productivity, innovation rates, decision-making speed, and reduced turnover. Effective knowledge management requires strong leadership support, an appropriate technology infrastructure, a collaborative culture, and continuous improvement processes that align knowledge practices with business goals and demonstrate a solid return on investment.

3. ANALYSIS AND DISCUSSION

This dataset presents knowledge management survey data from 30 respondents, which measures overall performance across four key dimensions and assessment scales. Knowledge sharing, knowledge creation, knowledge storage, and knowledge application receive ratings from 4 to 9, while knowledge management performance scores range from 53 to 98. The data reveal strong positive correlations between the four knowledge management practices and overall performance. Organizations that score high on all dimensions (range 8-9) consistently achieve performance scores above 85, with a peak of 98 when all practices score 9. Conversely, low ratings (range 5-6) correspond to performance scores below 70, with a minimum of 53. This pattern suggests that balanced implementation across all four practices yields the best results. Knowledge creation and knowledge application appear to be particularly influential, as high scores in these areas are associated with strong overall performance, indicating that generating new insights and applying knowledge in practice drive organizational success more significantly than simply storing or sharing information.

TABLE 1. Knowledge Management Descriptive Statistics

	Knowledge Sharing	Knowledge Creation	Knowledge Storage	Knowledge Application	Knowledge Management Effectiveness
count	30.0000	30.0000	30.0000	30.0000	30.0000
mean	7.0667	7.2333	7.0000	7.0333	77.9667
std	1.3113	1.1351	1.1447	1.4499	12.9148
min	5.0000	5.0000	5.0000	4.0000	53.0000
25%	6.0000	6.2500	6.0000	6.0000	68.5000
50%	7.0000	7.0000	7.0000	7.0000	79.5000
75%	8.0000	8.0000	8.0000	8.0000	88.7500
max	9.0000	9.0000	9.0000	9.0000	98.0000

Table 1 presents descriptive statistics for the knowledge management dimensions from 30 organizational respondents. The four knowledge management practices of sharing, creation, storage, and use show similar distributions with means ranging from 7.00 to 7.23, with scores ranging from 4-5 (minimum) to 9 (maximum). Knowledge creation has the highest mean at 7.23, indicating that organizations prioritize the generation of new insights. Standard deviations between 1.14 and 1.45 indicate moderate variation in how organizations implement these practices. Mean values of 7.0 across all dimensions indicate that half of the organizations score at or above this midpoint, while the 75th percentile at 8.0 indicates that the 75th percentile achieves strong performance quarter-over-quarter. Knowledge management performance shows a mean of 77.97, with significantly higher variability (standard deviation of 12.91) ranging from 53 to 98 points. The intermediate range of 68.5 to 88.75 shows substantial performance differences between organizations, indicating that even modest improvements in knowledge management practices can yield significant performance gains.

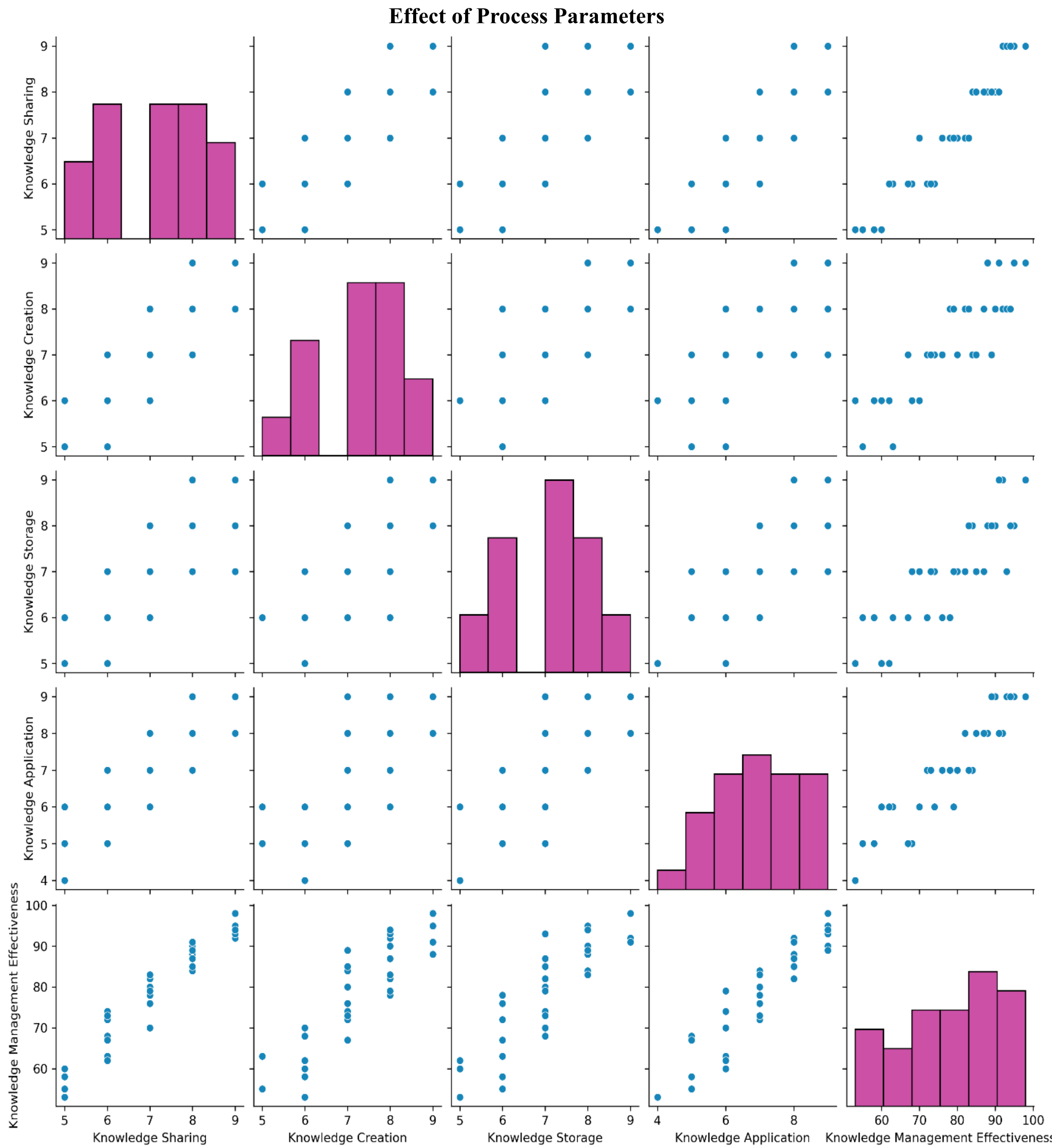

FIGURE 1. Knowledge Management Pair plot

Figure 1 This pair of graphs visualizes the relationships between all knowledge management variables through histograms and scatter plots. The diagonal plots show the spread of each variable, mainly centered around 7-8 for the four practices and 70-90 for performance. The off-diagonal scatter plots reveal strong positive linear relationships between all variables, with tighter clustering at higher values, indicating that organizations that excel in multiple practices achieve better performance scores.

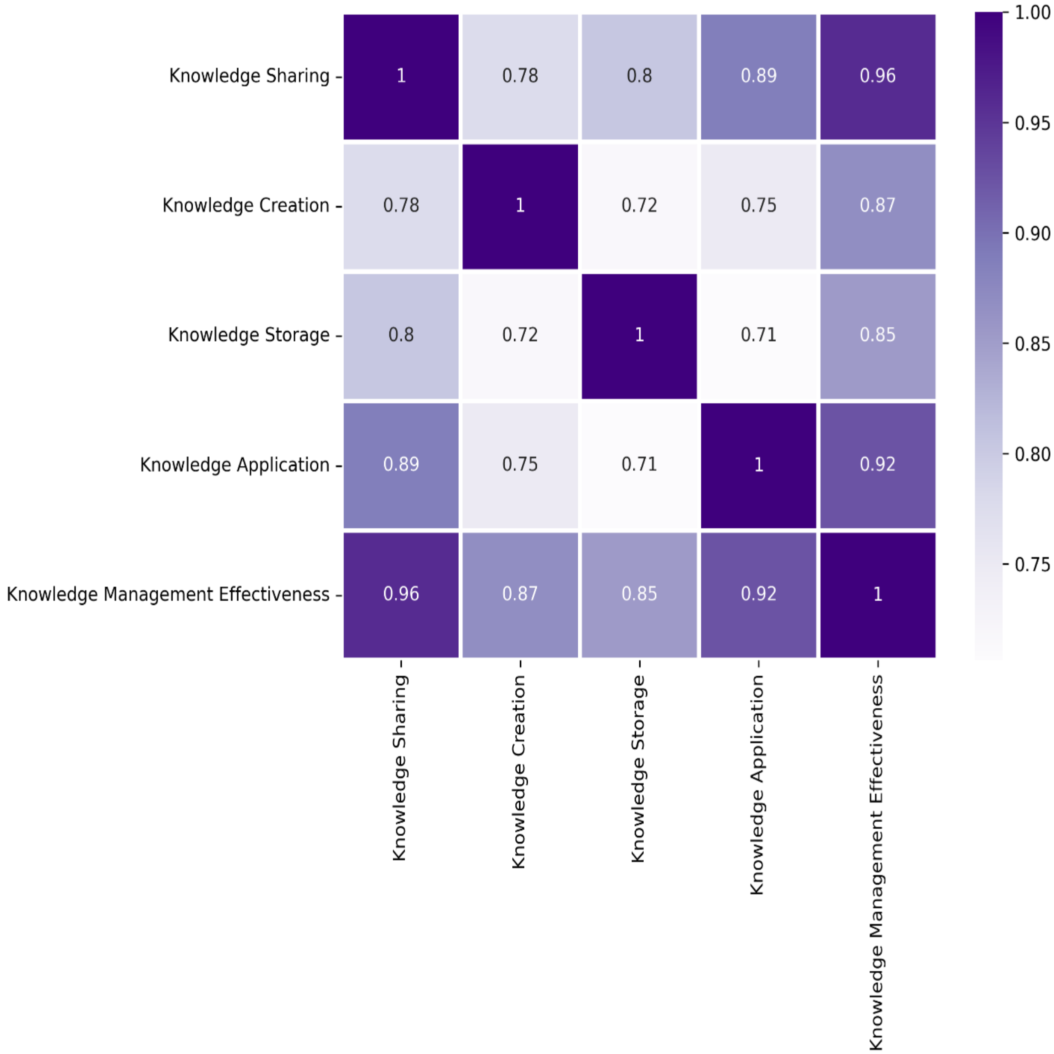

FIGURE 2. Knowledge Management Correlation heatmap

Figure 2 The correlation heat map shows the relationship strengths using color intensity from light (weak) to dark purple (strong). Knowledge sharing shows the strongest correlation with performance at 0.96, followed by knowledge utilization at 0.92. All four practices exhibit strong interrelationships (0.71-0.89), indicating that they function interdependently. Consistently high correlations with performance (0.85-0.96) confirm that all dimensions contribute significantly to organizational knowledge management success.

TABLE 2. Linear Regression Knowledge Management Effectiveness Train and Test performance metrics

	Model	Data	R2	EVS	MSE	RMSE	MAE	Max Error	MSLE	Med AE
Knowledge Management Effectiveness	Linear Regression	Test	0.9827	0.9894	3.8546	1.9633	1.5312	3.6282	0.0008	0.9419
		Train	0.9763	0.9763	2.8497	1.6881	1.4107	3.4959	0.0006	1.1142

Table 2 shows the performance of the linear regression model in predicting knowledge management performance, demonstrating excellent results for both the training and testing datasets. The model achieves an impressive R^2 of 0.9763 on the training data and 0.9827 on the testing data, indicating that it accounts for more than 98% of the variance in knowledge management performance. This distinct pattern of test performance outperforming training performance indicates strong generalization without overfitting. The error measures are exceptionally low in both datasets. The test data shows a root mean square error of 1.96 and a mean absolute error of 1.53, indicating that the predictions generally deviate from the true values by less than two points. The mean absolute error of 0.94 shows that half of the predictions fall within one point of the true values. The maximum errors in both datasets are below 3.7 points. These findings confirm that linear regression successfully captures the relationship between knowledge management practices and organizational performance, providing highly accurate and reliable predictions.

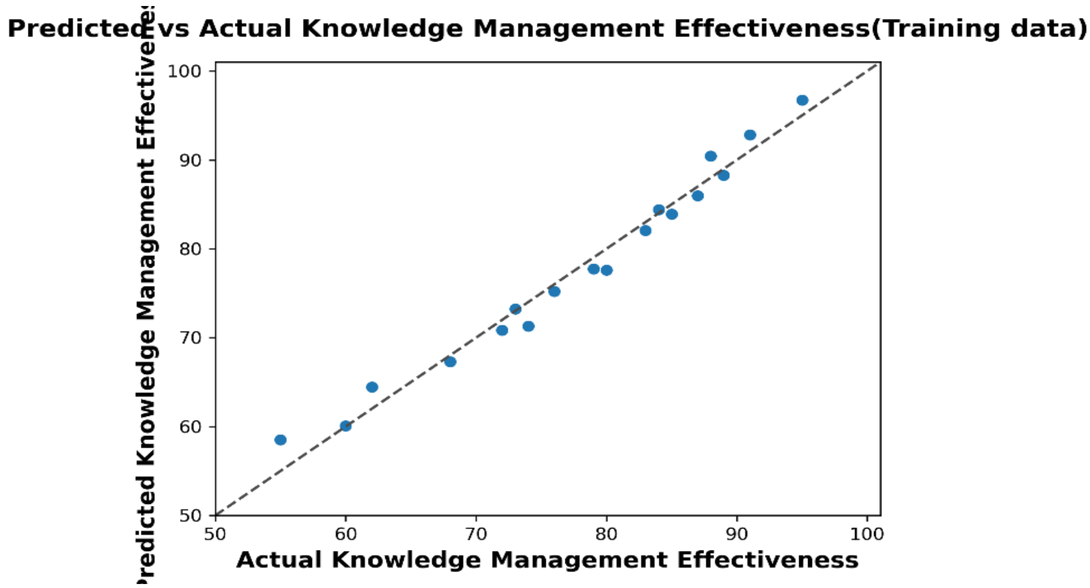

FIGURE 3. Linear Regression Knowledge Management Effectiveness Training

Figure 3 This scatterplot compares the actual and predicted performance scores for the training data. The points are tightly clustered along the diagonal reference line, indicating near-perfect prediction accuracy. The spread ranges from approximately 55 to 98, with minimal deviation from the best-fit line. This exceptionally close alignment demonstrates that the linear regression model successfully captured the underlying relationships without significant prediction errors in the training dataset.

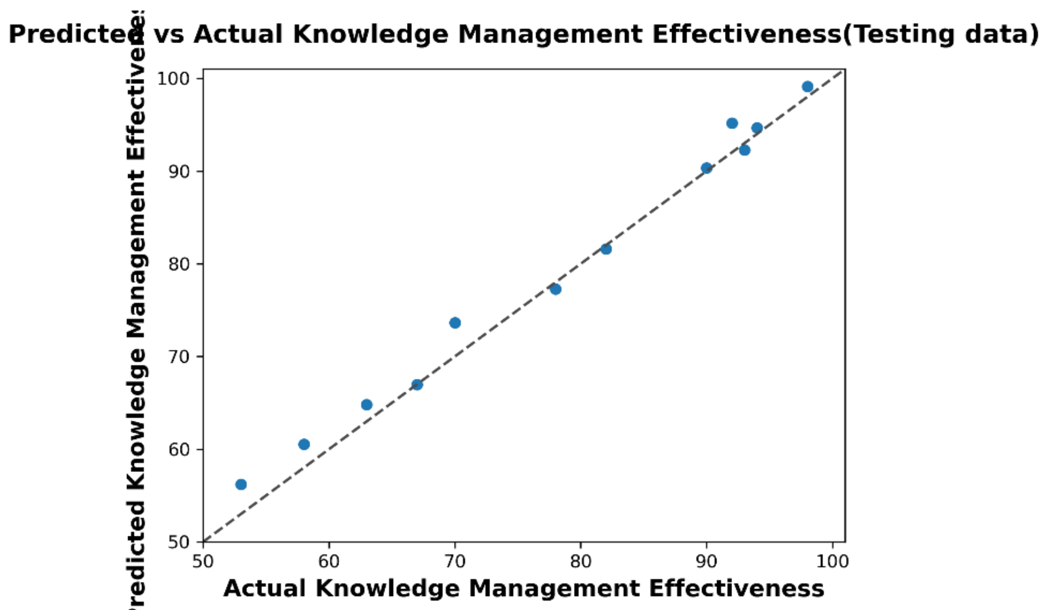

FIGURE 4. Linear Regression Knowledge Management Effectiveness Testing

Figure 4 The experimental data prediction graph shows the actual and predicted values for the missing data. The points are closely aligned with the diagonal reference line, demonstrating excellent generalization ability. The predicted values accurately track the actual scores over the entire range from 55 to 100, with only small deviations. This strong performance on new data confirms the model's reliability and its practical use for predicting knowledge management performance.

TABLE 3. Gradient Boosting Regression Knowledge Management Effectiveness Train and Test performance metrics

	Model	Data	R2	EVS	MSE	RMSE	MAE	Max Error	MSLE	Med AE
Knowledge Management Effectiveness	Gradient Boosting Regression	Train	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		Test	0.9283	0.9439	15.9564	3.9945	2.8409	9.1863	0.0032	1.9198

Table 3 illustrates the performance of the slope-increasing regression model in predicting knowledge management performance on the training and testing datasets. The training data shows flawless scores on all metrics, with both the R^2 and explained variance score reaching 1.0000, and all error metrics at zero, indicating that the model has fully captured the training patterns. However, the experimental performance reveals a very realistic predictive ability with an R^2 of 0.9283, indicating that the model accounts for approximately 93% of the variance in the unobserved data. The experimental measurements show moderate errors: the root mean square error is 3.99, the mean absolute error is 2.84, and the mean absolute error is 1.92, indicating that the typical predictions differ from the true values by less than 3-4 points. The maximum error of 9.19 indicates a poor prediction. Although the correct training performance indicates possible overfitting, the robust test results with R^2 demonstrate that the model effectively generalizes and reliably predicts knowledge management performance based on the four input dimensions.

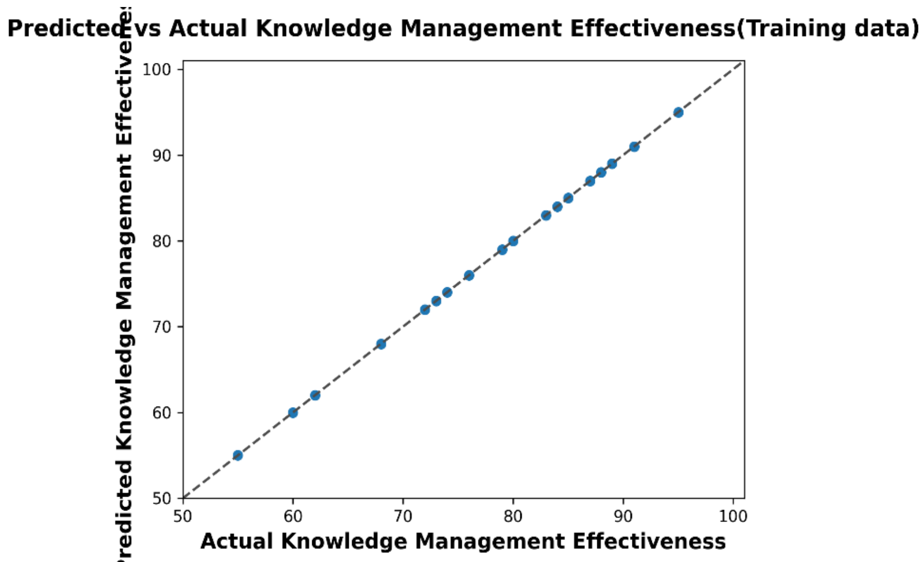

FIGURE 5. Gradient Boosting Regression Knowledge Management Effectiveness Training

Figure 5 The slope-increasing training plot shows perfect prediction accuracy, with all points precisely positioned on the diagonal line. This flawless alignment across the 55-98 score range indicates that the model has fully memorized the training patterns. While demonstrating the algorithm's powerful learning ability, this perfect fit raises concerns about potential overfitting, necessitating careful evaluation of experimental performance to assess true generalization ability.

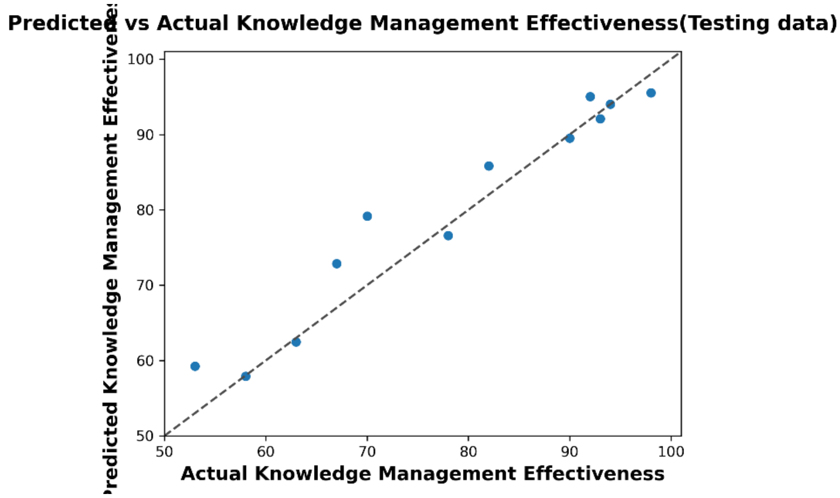

FIGURE 6. Gradient Boosting Regression Knowledge Management Effectiveness Testing

Figure 6 The slope-increasing test scheme yields good but imperfect predictions on the unseen data. Most of the points cluster near the diagonal line, although some scatter is visible, particularly in the range 60-80. Although a perfect fit to the training data is not achieved, the predictions are reasonably accurate across the performance spectrum. This performance gap between training and testing confirms that some overfitting has occurred, although the model still demonstrates strong predictive ability.

4. CONCLUSION

This research shows that successful knowledge management depends on the harmonious integration of four essential dimensions: knowledge sharing, knowledge creation, knowledge storage, and knowledge application. The significant correlations identified between these practices and overall organizational performance confirm that knowledge management should be pursued in a comprehensive manner rather than focusing on isolated components. Organizations that score high on all dimensions consistently show superior performance, with scores above 85 points, while those with weak practices score below 70, highlighting significant performance gaps that effective knowledge management can address. The predictive modeling results confirm the utility of both traditional statistical methods and advanced machine learning approaches to understanding knowledge management dynamics. The exceptional performance of linear regression ($R^2 = 0.9827$) demonstrates that the relationship between knowledge management practices and performance is essentially linear and interpretable, making it accessible for practical organizational application. The slope-increasing regression, although showing signs of overfitting in training, still achieved strong generalization ($R^2 = 0.9283$), confirming the strength of these relationships across different analytical frameworks. Of particular note is that knowledge sharing and knowledge utilization show strong correlations with performance at 0.96 and 0.92, respectively. This suggests that organizations should focus specifically on facilitating not only the creation and storage of knowledge, but also its dissemination and practical application. The cultural and behavioral dimensions of knowledge sharing, combined with ensuring that knowledge actually informs decision-making and problem-solving, emerge as the most important success factors. In an era where intellectual capital increasingly determines competitive advantage, these findings provide actionable guidance for organizations to design or refine their knowledge management strategies.

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