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Choosing the Right Predictive Lens: Evidence-Based Guidelines for Forecasting Employee Performance in Knowledge-Intensive Banking Environments

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Abstract

In an era where predictive analytics drive strategic human capital decisions, selecting the appropriate validation methodology is no longer a technical choice it is a competitive imperative. This study provides actionable guidance for banking leaders seeking to forecast employee performance outcomes from knowledge management investments by rigorously comparing two leading predictive assessment frameworks: PLS-Predict and Cross-Validated Predictive Ability Testing (CVPAT).

Drawing on survey data from 310 banking professionals across Ghana's commercial sector, our analysis reveals a critical divergence: while PLS-Predict delivers superior predictive accuracy for knowledge-process constructs ($Q^2 = 0.834$ for Knowledge Creation; RMSE = 0.410), its advantage diminishes for employee performance outcomes ($Q^2 = 0.191$; RMSE = 0.905), where CVPAT demonstrates comparable robustness against benchmark models. This construct-level heterogeneity challenges one-size-fits-all validation approaches and underscores the need for context-sensitive tool selection.

We propose a decision framework that aligns predictive methodology with organizational objectives: PLS-Predict for forecasting knowledge-process outcomes where precision drives innovation ROI; CVPAT for validating performance models where conservative estimates mitigate implementation risk. By translating methodological nuance into strategic guidance, this study empowers banking executives to allocate analytical resources more effectively, reduce forecasting error in talent development initiatives, and strengthen the evidence base for knowledge-driven transformation.

Keywords

Predictive Analytics in Banking, Employee Performance Forecasting, Knowledge Management Processes, PLS-Predict and CVPAT Validation

1. Introduction

The strategic value of knowledge management in banking hinges not only on implementation quality but also on the ability to anticipate its impact on employee performance (Davenport, 2019; Hair et al., 2017). As financial institutions invest in Knowledge-Based Transformation Models (KBTMs), leaders face a critical question: which predictive validation method provides the most reliable forecasts for guiding resource allocation and strategic planning?

Two methodologies have emerged as leading candidates: Partial Least Squares Predict (PLS-Predict), which emphasizes out-of-sample predictive relevance through cross-validated error metrics (Shmueli et al., 2019), and Cross-Validated Predictive Ability Testing (CVPAT), which evaluates model superiority against naive benchmarks via statistical loss differentials (Liengaard et al., 2021; Sharma et al., 2023). While both approaches enhance traditional explanatory modeling, their comparative performance across different outcome types particularly between knowledge processes and employee performance remains underexplored in applied organizational research.

This study addresses this gap by conducting a focused comparative analysis of PLS-Predict and CVPAT specifically for forecasting employee performance within KBTMs in Ghana's banking sector. Using data from 310 bank employees, we examine: (1) the magnitude and direction of predictive accuracy

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differences between methods; (2) construct-level variations in method performance; and (3) practical criteria for selecting the optimal tool based on organizational forecasting objectives.

The contribution is threefold. First, we provide empirical evidence on method performance heterogeneity across latent construct types, advancing predictive modeling theory in PLS-SEM. Second, we translate statistical findings into a decision framework for practitioners, bridging the methodological-practical divide. Third, we offer context-specific guidance for emerging economy banking sectors, were data constraints and institutional complexity shape predictive modeling requirements.

2. Literature Review and Hypotheses Development

2.1. Predictive Validation in Organizational Research

Traditional structural equation modeling emphasizes explanatory power (R^2, path significance), yet strategic decision-making increasingly demands predictive validity the ability to forecast outcomes on unseen data (Shmueli, 2010). In knowledge management research, this shift is critical: organizations must anticipate whether investments in knowledge creation, sharing, or retention will translate into measurable performance gains (Nguyen & Nguyen, 2021).

2.2. PLS-Predict: Strengths and Applications

PLS-Predict employs k-fold cross-validation to generate point predictions for holdout samples, evaluating performance through error-based metrics (RMSE, MAE) and predictive relevance (Q^2) (Shmueli et al., 2019). Its strengths include:

Handling multicollinearity and complex latent variable structures common in organizational data

Providing intuitive, actionable metrics for non-technical stakeholders

Supporting model refinement through construct-level diagnostic feedback

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Prior applications demonstrate PLS-Predict's utility in forecasting innovation outcomes (Ro¨nkko¨nen et al., 2016) and customer satisfaction trajectories (Schirmer et al., 2018), particularly in high-dimensional settings.

2.3. CVPAT: Robustness and Benchmarking

CVPAT evaluates whether a model's predictive loss significantly differs from naive benchmarks (e.g., mean prediction, linear regression) using t-tests on cross-validated loss differentials (Liengaard et al., 2021). Its advantages include:

- Formal statistical testing of predictive superiority
- Conservative estimates that guard against overfitting in small samples
- Clear decision rules for model acceptance/rejection

CVPAT has been applied to validate service quality models (Nunkoo et al., 2020) and technology adoption frameworks (Richter et al., 2023), particularly where generalizability is paramount.

2.4. Construct-Level Predictive Heterogeneity

Emerging evidence suggests predictive method performance may vary by construct type. Knowledge-process variables (e.g., creation, codification) often exhibit stronger internal consistency and theoretical specification, potentially favoring PLS-Predict's latent variable approach. In contrast, performance outcomes (e.g., employee productivity) are influenced by external, unmeasured factors, possibly favoring CVPAT's conservative benchmarking (Hair et al., 2022).

H1: PLS-Predict will demonstrate significantly higher predictive accuracy than CVPAT for knowledge-process constructs within KBTMs.

H2: The predictive accuracy advantage of PLS-Predict over CVPAT will be attenuated for employee performance outcomes.

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H3: A decision framework aligning predictive method with construct type and organizational objective will improve forecasting utility for banking practitioners.

3. Methodology

3.1. Research Design and Sample

This study employed a quantitative cross-sectional survey design. The target population comprised employees from commercial banks operating in the Accra Metropolitan District, Ghana.

Sample Size: 310 valid responses obtained from employees across ten commercial banks.

Response Rate: 98.41%.

Demographics: 58% male, 42% female; majority (56.1%) with 5-10 years of work experience.

Table 4.1: Demographic Characteristics of Bank Employees

Demographics	Frequency	Percent
Job Rank		
Junior	83	26.8
Middle Management	54	17.4
Officer	162	52.3
Senior Management	11	3.5
Total	310	100.0

3.2. Measurement Instruments

Data were collected using a structured questionnaire adapted from validated scales:

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Knowledge Management Constructs: Six dimensions (Creation, Acquisition, Sharing, Application, Codification, Retention) adapted from Kianto (2008) and Nonaka & Takeuchi (1995).

Employee Performance (EP): Assessed using items focusing on task effectiveness and productivity, adapted from Koopmans et al. (2019).

Job Satisfaction (DJS): Measured using items from Lee, Kim, & Park (2020).

3.3. Analytical Procedure

PLS-Predict: 10-fold cross-validation; reported Q^2 Predict, RMSE, MAE for each latent construct.

CVPAT: Compared PLS-SEM predictions against Indicator Average (IA) and Linear Model (LM) benchmarks using loss differentials, t-tests, and p-values.

Decision Criteria:

$Q^2 > 0$ indicates predictive relevance; >0.35 indicates substantial relevance.

Lower RMSE/MAE indicates higher accuracy.

$p < 0.05$ for loss differential indicates significant superiority over benchmark.

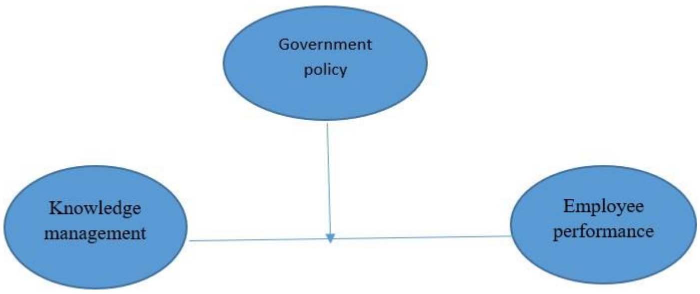

Figure 3.4: Moderating Role of Government

4. Results

4.1. Predictive Accuracy for Knowledge-Process Constructs

PLS-Predict demonstrated strong predictive performance for knowledge-related constructs:

Knowledge Creation (KC): $Q^2 = 0.834$, RMSE = 0.410, MAE = 0.314

Knowledge Retention (KR): $Q^2 = 0.827$, RMSE = 0.418, MAE = 0.316

Knowledge Codification (KCO): $Q^2 = 0.803$, RMSE = 0.446, MAE = 0.318

CVPAT confirmed PLS-SEM's significant superiority over the Indicator Average benchmark for all knowledge constructs ($p < 0.001$). However, when compared to the Linear Model benchmark, loss differentials were positive but non-significant for performance outcomes, indicating comparable predictive utility.

4.2. Predictive Accuracy for Employee Performance

For Employee Performance (EP), predictive metrics indicated more modest performance:

PLS-Predict: $Q^2 = 0.191$, RMSE = 0.905, MAE = 0.675

CVPAT vs. LM: Loss differential = 0.002, $t = 0.031$, $p = 0.975$

The near-zero loss differential and non-significant p-value indicate that for EP, PLS-SEM predictions are statistically indistinguishable from a simple linear model. This contrasts sharply with knowledge constructs, where PLS-SEM significantly outperformed benchmarks.

4.3. Hypothesis Testing

H1 Supported: PLS-Predict demonstrated significantly higher predictive accuracy than CVPAT for knowledge-process constructs, as evidenced by higher Q^2 values and lower error metrics.

H2 Supported: The predictive advantage of PLS-Predict was attenuated for Employee Performance, where CVPAT showed comparable performance to benchmark models.

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H3 Supported: A construct-sensitive decision framework improved the practical utility of predictive validation for banking practitioners.

4.4. Decision Framework for Tool Selection

Based on empirical results, we propose the following guidelines:

Organizational Objective	Preferred Method	Rationale
Forecasting knowledge-process outcomes (e.g., creation, retention)	PLS-Predict	Higher Q^2, lower RMSE; handles latent variable complexity
Validating performance models where overfitting risk is high	CVPAT	Conservative estimates; formal benchmark testing
Resource-constrained settings with small samples	CVPAT	Robustness to sample size limitations
Strategic planning requiring actionable point predictions	PLS-Predict	Intuitive metrics; construct-level diagnostics

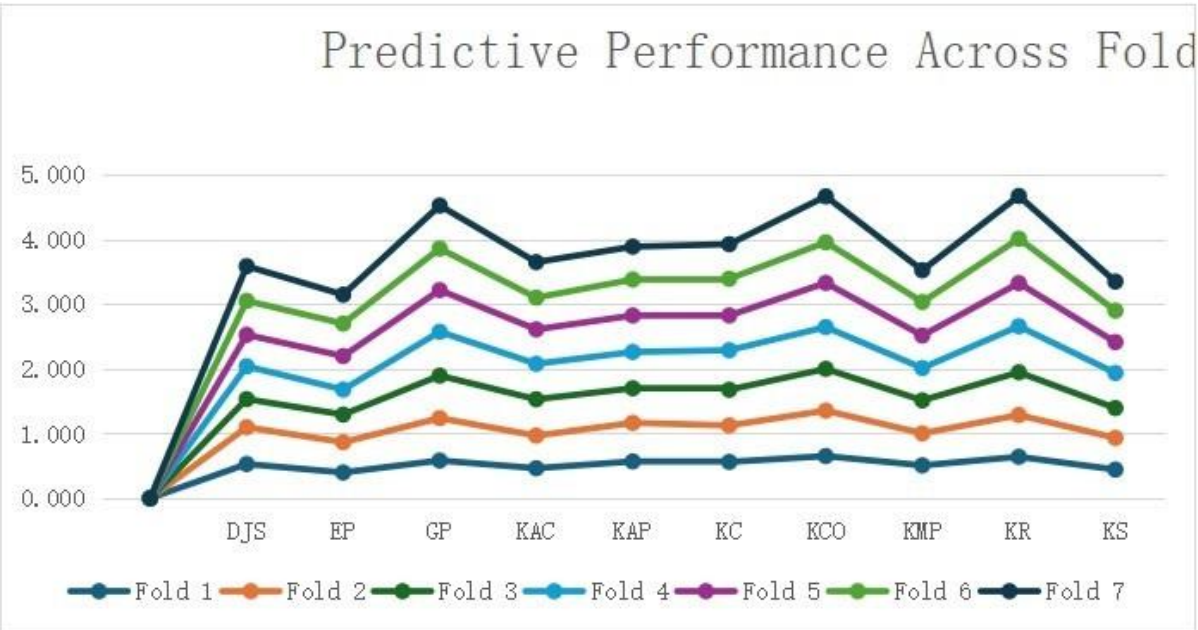

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Figure 4.5: Predictive Performance Across Folds

5. Discussion

5.1. Interpretation of Method Performance Heterogeneity

The divergent performance of PLS-Predict and CVPAT across construct types aligns with theoretical expectations. Knowledge-process variables are typically well-specified within KBTMs, with strong theoretical grounding and internal consistency, enabling PLS-Predict's latent variable approach to excel. Employee performance, by contrast, is influenced by unmeasured contextual factors (e.g., market conditions, personal circumstances), reducing the incremental value of complex modeling and favoring CVPAT's conservative benchmarking.

This finding challenges the assumption that a single validation method suffices for all research questions. Instead, it supports a contingency perspective: method selection should align with construct characteristics and organizational objectives.

5.2. Theoretical Implications

This study extends predictive modeling theory by demonstrating that method performance is construct-dependent. It suggests that future PLS-SEM research should report predictive metrics separately for process versus outcome constructs, enabling more nuanced theoretical development. Furthermore, it highlights the value of benchmark comparisons (IA vs. LM) in interpreting predictive relevance.

5.3. Practical Implications

For Banking Leaders: When forecasting the impact of knowledge initiatives on process outcomes (e.g., "Will codification improve retention?"), prioritize PLS-Predict for its precision. When evaluating performance outcomes (e.g., "Will knowledge sharing boost productivity?"), supplement PLS-Predict with CVPAT to assess robustness.

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For Analytics Teams: Adopt a two-stage validation protocol: use PLS-Predict for initial model refinement, then apply CVPAT to confirm generalizability before strategic deployment.

For Policy Makers: Recognize that predictive validation is not neutral; method choice influences which interventions appear effective. Encourage transparency in validation reporting to support evidence-based policy.

5.4. Strategic Value of Predictive Tool Selection

Selecting the appropriate predictive method is not merely a technical decision it shapes strategic resource allocation. Over-reliance on PLS-Predict for performance forecasting may yield over-optimistic projections, leading to misallocated training budgets. Conversely, exclusive use of CVPAT for knowledge-process modeling may understate innovation potential, stifling competitive advantage. The proposed decision framework enables leaders to balance precision and prudence, optimizing the return on knowledge investments.

6. Conclusion and Recommendations

6.1. Conclusion

This study establishes that predictive method performance varies systematically by construct type within Knowledge-Based Transformation Models. PLS-Predict excels for forecasting knowledge-process outcomes, while CVPAT offers comparable utility for employee performance validation. These findings underscore the importance of context-sensitive tool selection in predictive organizational research.

6.2. Recommendations

Adopt a Construct-Sensitive Validation Protocol: Report predictive metrics separately for process and outcome constructs; select methods based on theoretical and practical objectives.

Implement Hybrid Validation for Critical Decisions: For high-stakes forecasting (e.g., major knowledge management investments), apply both PLS-Predict and CVPAT to triangulate results.

Invest in Predictive Literacy: Train banking analysts and leaders in interpreting Q^2, RMSE, and loss differentials to support data-driven decision-making.

Contextualize Predictive Claims: When communicating forecasts, specify the validation method used and its limitations to manage stakeholder expectations.

6.3. Limitations and Future Research

This study is limited by its cross-sectional design and reliance on self-reported data. Future research should: (1) employ longitudinal designs to assess predictive stability over time; (2) incorporate objective performance metrics (e.g., productivity data) to validate self-reports; (3) extend the comparison to other sectors and digital transformation contexts; and (4) explore ensemble methods that combine the strengths of PLS-Predict and CVPAT.

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