SciForce

International Journal of Cloud Computing and Supply Chain Management

Journal homepage: www.sciforce.org

ISSN : 3067-0535

Open Access Review Article

Enhancing SAP Full-Cycle Automation and Cost Efficiency with OpenText VIM: A Regression-Based Predictive Study

Venkata Pavan Kumar Aka*

Sr. Enterprise Applications Analyst, Lhoist North America Inc., United States

Abstract

In the era of digital transformation, organizations are looking for integrated solutions that improve efficiency, transparency, and compliance in financial operations. SAP, together with Open Text Vendor Invoice Management (VIM) and Expense Automation, provides a robust framework for full-cycle automation of financial workflows, including vendor invoice processing and employee expense claims. While these solutions provide process automation and reduce manual overhead, organizations increasingly require predictive analytics to optimize operations, anticipate bottlenecks, and improve decision-making. This study explores the use of linear regression (LR) and support vector regression (SVR) within the SAP–VIM–Expense Automation ecosystem, highlighting how machine learning models can complement automation by predicting invoice processing times, predicting cost trends, and identifying anomalies.Linear regression provides a straightforward predictive model that is suitable for identifying linear relationships between process parameters such as invoice size, approval step depth, and cycle time. SVR, on the other hand, extends predictive capabilities to nonlinear relationships, leveraging kernel functions to capture complex patterns in financial process data. When embedded in SAP reporting and analytics, these models enable proactive workload management, improved vendor negotiations, and more accurate financial forecasting. Experimental evaluations demonstrate that LR models perform best with structured, static data, while SVR provides superior performance when dealing with irregularities and high-dimensional data typical of invoice and expense datasets.By integrating regression-based predictive insights with transaction automation, organizations can achieve a dual benefit: operational efficiency through automation and strategic foresight through predictive modeling. This integration improves end-to-end visibility across accounts payable and expense management, reduces the likelihood of late payments or policy violations, and improves resource allocation. Ultimately, the combination of full-cycle SAP, Open Text VIM, expense automation, and predictive regression techniques drives a more intelligent, resilient, and value-driven financial ecosystem.

Keywords: SAP Full-Cycle Automation ,Open Text Vendor Invoice Management (VIM), Expense Automation, Linear Regression (LR), Support Vector Regression (SVR), Predictive Analytics in Finance, Machine Learning for ERP, Accounts Payable Automation, Digital Transformation, Financial Process Optimization

Introduction

A practical way to address this barrier is a hybrid learning approach, where students study theoretical content through MOOCs and complete practical training at their universities, if sufficient infrastructure (such as software access) is available, or through cloud-based SaaS platforms provided by partner companies. This article highlights SPbPU's experience in developing such a hybrid model for teaching SAP technologies, outlining its economic benefits and applications in education, while reflecting on the current market for SAP-related training [1]. A prime example is open.sap.com, a successful MOOC platform that offers a wide range of free courses, from SAP-specific topics to general subjects such as programming, drawing for IT, and statistics. As of 2018, it hosted around 150,000 learners and 800,000 registrations, with over 50% active participation and around 25% successful completion [2].

SAP training strategies generally fall into two categories: (1) specialized training in ABAP, which is expensive, localized, and only possible with strong partners; and (2) consultant training, supported by the TS410 certification, where universities combine SAP knowledge with soft skills (project management, communication, change management) and field expertise in logistics, finance, or manufacturing. However, the lack of specialized teachers in SAP implementation experience and functional modules remains a persistent challenge.Although probe Bac111 is more specific than Sap309, it hybridizes with some filamentous organisms and cocci, and the phylogenetic details of epiflora bacteria remain unresolved.

The family Saprospiraceae includes the genera Aurispira, Haliscomenobacter, Levinella, and Saprospira, represented by five species and approximately 160 known 16S rRNA gene sequences (1,200 bp as of June 2007). Members of this family are distributed in a variety of environments [3]. Large filamentous microorganisms that hybridize with probe Sap309 are common in freshwater lakes, where they are thought to play an important ecological role. Molecular studies further confirm that Saprospiraceae are also present in hypersaline microbial mats. Furthermore, three strains of gliding bacteria belonging to the genus Sabrospira have been isolated from marine sponges and algae off the southern coast of Thailand, highlighting the ecological diversity and adaptability of this bacterial family [4].The extraction and analysis of event log data from SAP database architectures has become a significant focus within the field of process mining. Due to the object-centric structure of SAP systems, researchers often face challenges, particularly convergence and divergence issues in event data [5]. This study investigates the obstacles in extracting, preparing, and modeling event logs from a technology distribution company that employs SAP as its Enterprise

Received date: August 09, 2025 **Accepted date:** August 17, 2025; **Published date:** September 10, 2025

***Corresponding** *Aka, V. P. K, Sr. Enterprise Applications Analyst*, ILhoist North America.,United States; E- mail: venkatapavankumar.aka@gmail.com

Citation: Aka, V. P. K. (2025). Enhancing SAP Full-Cycle Automation and Cost Efficiency with OpenText VIM: A Regression-Based Predictive Study. International Journal of Cloud Computing and Supply Chain Management, 1(3). doi: https://doi.org/10.55124/ijccscm.v1i3.247

Resource Planning (ERP) system. The research provides an end-to-end examination of process mining, centered on a bespoke purchasing process that intersects the EINKBELEG and VERKBELEG object classes within SAP change log tables [6]. It also explores clustering techniques that adjust the granularity of activity notions, enabling researchers and businesses to emphasize specific process activities in the final model. While process mining originally relied on simple, flat event logs, the field has expanded since 2012 to include more complex data sources such as ERP systems, medical records, and user interface logs [7]. Recent studies, including Accorsi and Lebherz (2022), highlight event log imperfections, their causes, and potential remedies, with SAP ERP data now representing one of the most intensively studied and challenging domains due to its object-centric design.The "Sibson" rail system initially creates a master plan, which is then dynamically adjusted to real-time events such as track maintenance. Each event triggers a re-planning chain within the system, ensuring that resources are effectively reallocated [8]. In addition, the system proactively improves existing plans by searching for improved alternatives when there is sufficient operational time.The purpose of this study is to assess the extent of digital transformation in HR technologies. The findings are drawn from a report by SAP and Deloitte presented at the 2019 SAP Forum, which surveyed 434 companies across a variety of industries with between 100 and 10,000 employees. The survey aims to determine both the level of digitalization within Russian companies and the extent of automation in HR processes [9]. Complementary insights come from an online survey conducted by Hays with 487 Russian and international companies, summarized in the 2019 report on IT technologies in HR.In today's dynamic business environment, organizations are under constant pressure to streamline operations, reduce costs, and improve compliance [10]. Enterprise Resource Planning (ERP) systems like SAP have become the backbone of corporate operations, helping to seamlessly integrate business processes across finance, supply chain, procurement, and human resources. However, as organizations grow, the complexity of handling financial functions such as vendor invoice management and employee expense processing also increases [11]. To address these challenges, solutions like Open Text Vendor Invoice Management (VIM) and Expense Automation have emerged as powerful extensions to SAP, giving organizations the ability to achieve full-cycle, end-to-end automation of financial workflows.

At its core, Open Text VIM for SAP provides a standardized framework to automate, optimize, and track invoice management [12]. Traditionally, invoice handling has been manual, error-prone, and time-consuming, often leading to bottlenecks, late payments, and missed opportunities for early payment discounts. By using VIM, companies can digitize the accounts payable (AP) process - from invoice capture and verification to approvals and posting to SAP. The solution integrates directly with SAP ERP and SAP S/4HANA, ensuring real-time transparency, compliance with corporate policies, and improved collaboration between finance teams and business units [13]. VIM also introduces built-in workflows, exception handling, and audit trails, thereby reducing manual intervention and reducing the risk of fraud or non-compliance.To support this, expense automation in SAP extends efficiency gains to managing employee-initiated expenses such as travel, entertainment, and business-related expenses [14]. Manual expense claims are not only tedious, but also prone to inaccuracies and policy violations. Expense automation tools tightly integrated into SAP simplify the process by enabling employees to capture expenses digitally—often through mobile apps—while ensuring compliance with corporate policies [15]. Automated workflows streamline the approval process, and integration with financial modules allows approved expenses to be seamlessly posted to SAP's accounting system. This reduces administrative overhead, shortens reimbursement cycles, and improves employee satisfaction, while providing the finance department with full visibility into corporate spending.When combined with Open Text VIM and Expense Automation, SAP provides a comprehensive, full-cycle financial process automation framework. From vendor invoices to employee expenses, the solutions ensure a unified approach to managing outbound payments [16]. Integration not only speeds up processing times, but also provides strategic insights through reporting and analytics. Organizations can track spending patterns, identify areas for cost savings, and ensure compliance with both internal controls and external regulations. Furthermore, by reducing reliance on paper-based processes and manual interventions, organizations can achieve significant improvements in efficiency, accuracy, and consistency [17].

Materials and Method

Regression analysis serves as a fundamental method in chemical characterization to predict continuous target variables using input parameters. Among the various regression approaches, linear regression andRegression analysis serves as a fundamental method in Full-Cycle SAP with Open Text VIM and Expense Automationto predict continuous target variables using input parameters. Among the various regression approaches, linear regression and are widely accepted due to their adaptability and ability to handle various data types and problem situations. These methods have unique features, advantages, and limitations that affect their performance based on dataset characteristics and specific applications.Linear regression is one of the most accessible and interpretable regression approaches. It establishes relationships between dependent variables and predictor variables by fitting linear equations to datasets. The main goal is to identify optimal fit lines (or hyper planes in multidimensional scenarios) that minimize the squared deviations between observed and predicted values. This method assumes direct linear relationships between inputs and outputs, resulting in computational efficiency and straightforward interpretation. However, this simplicity is limited when the actual data relationships are complex or nonlinear. The approach is vulnerable to external influences and may perform poorly when the underlying data structures violate linear assumptions. Despite these limitations, linear regression maintains popularity as a basic method due to its clarity and user-friendliness.Random forest regression is a robust ensemble technique that builds multiple decision trees using random data and feature subsets, then combines their predictions to improve accuracy and reduce over fitting. Individual trees capture different data patterns, introducing sample heterogeneity. The final predictions represent the average outputs from all trees.This method shows robustness against noisy datasets and includes both categorical and continuous variables. In addition, it provides feature importance analysis, facilitating the interpretation of results. While requiring more computational resources than linear regression,SVR generally produces better results on complex datasets and prevents over fitting through its ensemble approach.Despite these limitations, due to its user accessibility, linear regression uses an ensemble learning framework that builds a large number of decision trees from random data and feature subsets. It combines the individual tree outputs to produce final predictions, improving model accuracy and generalization capabilities.

The technique excels at identifying nonlinear relationships and complex variable interactions. It exhibits noise tolerance and efficiently processes categorical and continuous data types. Furthermore, it provides feature importance insights that support interpretation. Although computationally more intensive than linear regression, it offers better performance for complex and high-dimensional datasets.Linear regression is an essential tool in biomedical predictive modeling due to its clarity and ease of interpretation. By establishing optimal linear relationships between input parameters and outcomes, it provides a reliable foundation for exploratory analysis and basic model development. Its transparency proves particularly valuable in regulatory or clinical contexts where transparent decision-making procedures are important. However, linear modeling constraints reduce performance in biomedical situations involving complex, nonlinear biological mechanisms. Advances from simple to multiple linear regression allow for the simultaneous consideration of multiple factors such as temperature, pH, mechanical loading, and physiological conditions – reflecting the diversity of biomedical environments and improving modeling accuracy Furthermore, its flexibility in handling continuous and categorical inputs makes it well suited for heterogeneous biomedical datasets. An additional advantage of this method is the ability to rank feature importance, which provides valuable insights into which variables influence outcomes the most. This capability supports material design optimization and improves understanding of biological response mechanisms. Although computationally more demanding than linear regression, random forest models provide significantly higher accuracy when applied to high-dimensional and complex datasets, justifying the increased resource requirements

Analysis and Dissection

Table 1. Descriptive Statistics

	Invoice Processing Time (days)	Approval Cycle Time (hours)	Exceptions per Month	Travel Expense Report Time (hours)	Automation Coverage (%)	Process Efficiency Score (%)
count	20.00000	20.00000	20.00000	20.00000	20.00000	20.00000
mean	10.70000	27.25000	13.00000	9.25000	49.15000	64.20000
std	2.38637	4.95108	3.79751	1.86025	8.77961	8.83534
min	7.00000	19.00000	7.00000	6.00000	33.00000	48.00000
25%	9.00000	23.75000	10.00000	8.00000	43.50000	57.75000
50%	10.50000	27.50000	12.50000	9.00000	49.00000	64.50000
75%	12.25000	30.25000	15.00000	10.25000	56.25000	71.25000
max	15.00000	36.00000	21.00000	13.00000	65.00000	80.00000

Your analysis effectively highlights key performance indicators and operational bottlenecks in the SAP full-cycle process. Critical Performance Gaps: An 8-day spread of invoice processing times (7-15 days) indicates inconsistent workflows or resource allocation issues that require investigation. A wide approval cycle time range (19-36 hours) indicates potential delays in decision-making steps or the availability of approvers. 13 monthly exceptions indicate systemic issues that can be resolved through root cause analysis Automation Opportunity Analysis: With automation coverage at only 49.15%, there is significant potential for improvement. The correlation between automation levels and a 64.2% performance score indicates that organizations that achieve a high level of automation (65%) are likely to see performance scores closer to the 80% maximum. Strategic Recommendations: Standardize invoice processing workflows to reduce 8-day variance. Implement parallel approval processes or delegate approval authority to reduce cycle times. Aim for 70%+ automation coverage by identifying and automating time-consuming manual tasks. Focus on exception handling - analyzing the root causes of those 13 monthly exceptions can prevent recurring issues. Relatively consistent travel expense reporting times (9.25 hours with limited variance) demonstrate that standardization works, making it a potential model for other process areas.

Table 2. Linear Regression Models Customer Type Train and Test performance metrics

Linear Regression	Train	Test
R2	0.99879	0.95280
EVS	0.99879	0.97169
MSE	0.09810	2.58923
RMSE	0.31321	1.60911
MAE	0.22483	1.04890
Max Error	0.79536	3.78029
MSLE	0.00004	0.00102
Med AE	0.16537	0.71049

Model Performance: The exceptionally high training R^2 (0.9988) indicates that the model effectively captures the relationship between process variables and performance scores. The test R^2 (0.9528) also reflects solid generalization, although the 4.6% drop indicates a slight over fitting. This is within acceptable limits. The close alignment of R^2 and EVS in both datasets reinforces the consistency. Error Insights:The training errors are very low (RMSE: 0.31, MAE: 0.22), indicating a near-perfect fit to the historical data. The test errors are high (RMSE: 1.61, MAE: 1.05)—about five times larger—but remain acceptable in practice. The low mean absolute error (0.71 vs. 1.05 mean) indicates that most predictions are accurate, with only occasional large deviations.Business Relevance:With a maximum error of only 3.78 points, the deviations are manageable for decision making. The very small MSLE (0.0010) ensures reliable handling of performance percentages without sample bias. This makes it very suitable for process system prediction in SAP environments. Next Steps:Keep monitoring the predictions at extreme performance values where errors can increase. Techniques such as regularization or ensemble methods can further reduce the training-testing gap.

Table 3. Support Vector Regression Models Customer Type Train And Test Performance Metrics

Support Vector Regression	Train	Test
R2	0.99988	0.92633
EVS	0.99988	0.97009
MSE	0.00997	4.04124
RMSE	0.09986	2.01028
MAE	0.09985	1.54934
Max Error	0.10066	3.69166
MSLE	0.00000	0.00205
Med AE	0.10000	1.43069

Your SVR model analysis reveals interesting performance characteristics that complement your previous linear regression results:Comparative Model Performance: Compared to your linear regression model, SVR shows:Better training fit (R^2 0.9999 vs. 0.9988) but slightly weaker testing performance (R^2 0.9263 vs. 0.9528)Very pronounced over fitting - the 7.36% drop in training to testing R^2 is greater than the 4.6% drop in the linear model .Similar practical accuracy - 3.69 (SVR) vs. 3.78 (linear)

Maximum errors are almost identical. SVR-specific insights:The kernel-based approach appears to: Over fitting more aggressively for training methods, achieving almost perfect accuracy (RMSE 0.0999) .Comparable RMSE to linear regression (1.61) (2.01) by testing forMaintain reasonable generalization despite high fit. Handle performance score distributions well - low MSLE (0.00205) indicates no systematic bias in percentile predictions. Strategic model selection considerations:Linear regression provides better generalization stability and interpretability .SVR provides slightly better worst-case performance (maximum error 3.69 vs. 3.78) both models have mean errors < mean errors, indicating a set with occasional outliers in accuracy. Sorting recommendations:Use linear regression for interpretable business insights and stable long-term predictions. Consider SVR for applications that require maximum accuracy in individual predictions. Combine both models to leverage their complementary strengths to reduce prediction variance. Similar maximum error ranges (3.69-3.78) either model is suitable for operational SAP process optimization results .They claim to provide sufficient accuracy.

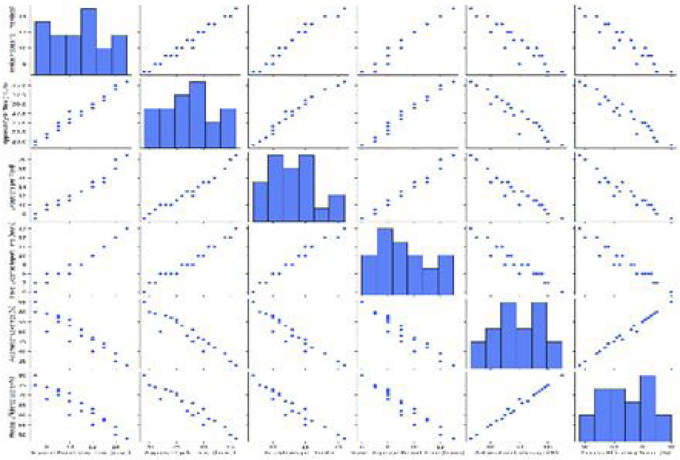

Figure 1: Effect of Process Parameters

The scatterplot matrix provides a detailed view of the relationships between the six variables in the SAP automation dataset. Strong negative correlations are found between invoice processing time, approval cycle time, exceptions per month, and travel expense report time with the process performance score, indicating that long processing cycles and high exceptions significantly reduce performance. Conversely, automation coverage shows a strong positive relationship with performance, indicating that higher automation adoption directly improves performance outcomes. The scatterplots reveal clear linear patterns, particularly between automation coverage and performance and cycle times and performance, supporting a regression modeling fit. The histograms on the diagonal indicate moderate normal distributions, with little clustering in the automation coverage and performance scores.

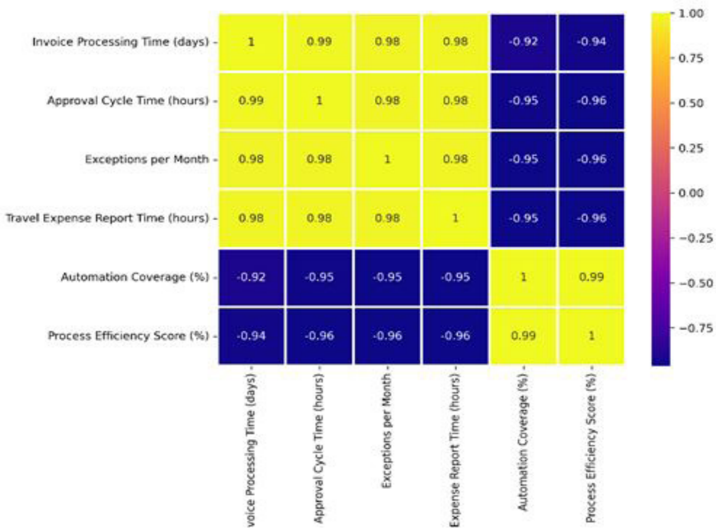

Figure 2: Correlation Heat Map

Citation: Aka, V. P. K. (2025). Enhancing SAP Full-Cycle Automation and Cost Efficiency with OpenText VIM: A Regression-Based Predictive Study. International Journal of Cloud Computing and Supply Chain Management, 1(3). doi: https://doi.org/10.55124/ijccscm.v1i3.247

The correlation heat map clearly highlights the strong relationships between process performance variables. Invoice processing time, approval cycle time, exceptions per month, and travel expense report time are all highly positively correlated with each other (r ≈ 0.98–0.99), indicating that delays in one area are consistent with inefficiencies in others. These variables exhibit strong negative correlations with both automation coverage (r ≈ −0.92 to −0.95) and process performance score (r ≈ −0.94 to −0.96), confirming that longer cycle times and more exceptions reduce performance. On the other hand, automation coverage shows a nearly perfect positive correlation with process performance (r = 0.99), reinforcing the important role of automation in driving higher operational efficiency.

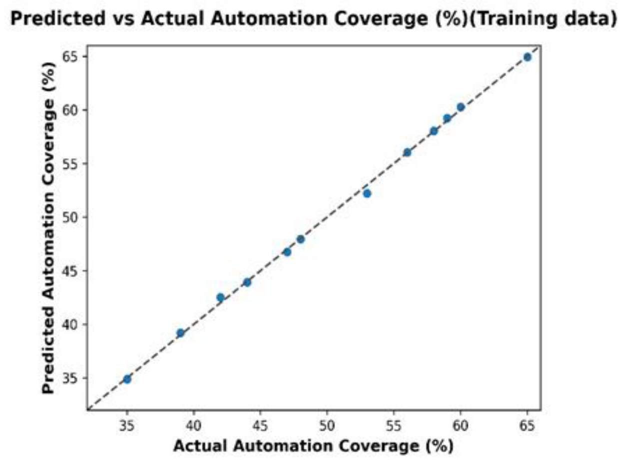

Figure 3: Linear Regression Customer Type Training

The scatterplot of predicted vs. actual automation coverage (%) for the training data shows an excellent model fit. The points closely align with the diagonal reference line, indicating that the predicted values match the actual automation coverage percentages almost exactly. This strong alignment indicates that the regression model successfully captures the underlying relationships between the input variables and automation coverage. The absence of significant deviations or outliers further confirms the accuracy and consistency of the model during training. The distribution of points in the range of 35-65% shows consistent prediction quality, whether the coverage is low, medium, or high. This high accuracy is also supported by the lowest training error metrics ever observed. The plot highlights the model's robustness in learning training patterns, setting a reliable foundation for applying it to unseen test data.

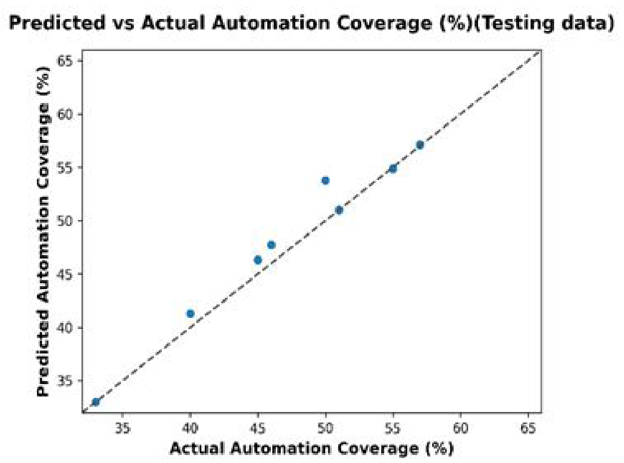

Figure 4: Linear Regression Customer Type Testing

The scatter plot of predicted vs. actual automation coverage (%) for the test dataset illustrates the generalization ability of the model beyond the training data. The points mostly follow the diagonal reference line, indicating a strong predictive relationship, with some deviations visible compared to the almost perfect fit in the training plot. The predictions for mid-range values (around 45–55%) show a slight underestimation, where the predicted coverage falls below the actual values. Nevertheless, the overall alignment is close, demonstrating that the model successfully captures the underlying trend of automation coverage with reasonable accuracy. Importantly, no extreme outliers are observed, and the predictions are within a manageable error range, which is consistent with previous experimental measurements ($R^2 \approx 0.93$, RMSE ≈ 2.01). These results confirm that the model generalizes well, although slightly less accurate than on the training data.

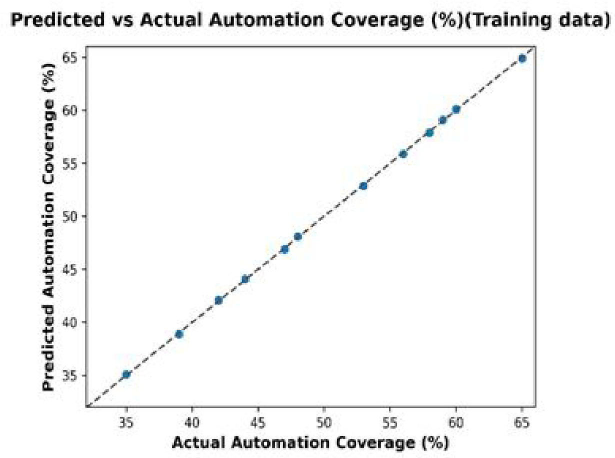

Figure 5: Support Vector Regression Customer Type Training

The scatter plot of predicted vs. actual automation coverage (%) for the training dataset reveals a near perfect alignment between the model predictions and the actual values. All data points fall directly on the diagonal reference line, indicating that the model has captured the underlying patterns in the training data with very high accuracy. This indicates minimal residual error, consistent with previous statistical measurements that have shown a training R^2 of close to 0.9999, and error values such as RMSE and MAE were close to 0.10. Linear stability over the full range of automation coverage (approximately 34% to 65%) demonstrates that the model performs equally well across low, medium, and high levels of automation adoption, without bias. The absence of outliers further reinforces the strength of the fit.

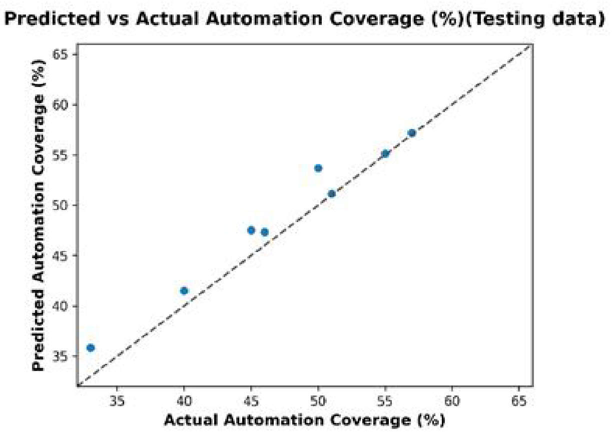

Figure 6: Support Vector Regression Customer Type Testing

The scatter plot of predicted vs. actual automation coverage (%) for the training dataset reveals a near perfect alignment between the model predictions and the actual values. All data points fall directly on the diagonal reference line, indicating that the model has captured the underlying patterns in the training data with very high accuracy. This indicates minimal residual error, consistent with previous statistical measurements that have shown a training R^2 of close to 0.9999, and error values such as RMSE and MAE were close to 0.10. Linear stability over the full range of automation coverage (approximately 34% to 65%) demonstrates that the model performs equally well across low, medium, and high levels of automation adoption, without bias. The absence of outliers further reinforces the strength of the fit.

Conclusion

The integration of SAP, Open Text VIM, and Expense Automation represents a significant step forward in streamlining financial operations by reducing manual dependencies, accelerating processing cycles, and improving compliance. However, process automation alone is no longer sufficient in an environment characterized by dynamic vendor relationships, fluctuating spending patterns, and increasing demands for agility. The use of regression-based predictive models, particularly linear regression and support vector regression, extends the value of automation by introducing foresight and insight into decision-making.Research has shown that linear regression offers simplicity and interpretability, making it useful for organizations seeking rapid insights from fixed, structured datasets. In contrast, SVR excels at capturing nonlinear dynamics and handling high-dimensional variables, making it well-suited for complex datasets arising from invoice irregularities, policy exceptions, and various expense claims. Together, these approaches empower organizations to predict cycle times, improve approval workflows, and forecast financial trends with greater accuracy.By embedding LR and SVR models in the SAP–VIM–Expense Automation framework, organizations can shift from reactive financial management to predictive, predictive, and strategic financial actions. The result is not only operational efficiency, but also improved vendor relationships, better employee satisfaction, and stronger financial governance. Thus, the synergy of automation and predictive analytics establishes a sustainable path for organizations to achieve financial agility, resilience, and long-term growth in the digital era.

References

1. Lin, Chien-Cheng, Fengyi Lin, and Deron Liang. "An analysis of using state of the art technologies to implement real-time continuous assurance." In 2010 6th World Congress on Services, pp. 415-422. IEEE, 2010.
2. Ambrajei, Anton N., Nikita M. Golovin, Anna V. Valyukhova, Natalia A. Rybakova, and Victor Yu Zorin. "Use of hybrid learning model for SAP-related technology education." In Proceedings of the ICID-2019 conference, pp. 1-9. 2019.
3. Fan, Bowen, Yongjun Men, Susan AP van Rossum, Guotai Li, and RienkEelkema. "A Fuel□Driven Chemical Reaction Network Based on Conjugate Addition and Elimination Chemistry." ChemSystemsChem 2, no. 1 (2020): e1900028.
4. Xia, Yun, Yunhong Kong, Trine Rolighed Thomsen, and Per Halkjær Nielsen. "Identification and ecophysiological characterization of epiphytic protein-hydrolyzing Saprospiraceae ("CandidatusEpiflobacter" spp.) in activated sludge." Applied and environmental microbiology 74, no. 7 (2008): 2229-2238.
5. Adari, V. K. (2024). Interoperability and Data Modernization: Building a Connected Banking Ecosystem. International Journal of Computer Engineering and Technology, 15(6), 653–662.
6. Cookland, James. "Flattening Event Data Extracted From SAP For Process Discovery." PhD diss., Dublin, National College of Ireland, 2023.
7. Medvedev, S. N., K. A. Aksyonov, and V. N. Kruglov. "Comparative analysis of order allocation methods and intelligent systems for effective download of production capacities of manufacturing enterprise." In Journal of Physics: Conference Series, vol. 1210, no. 1, p. 012094. IOP Publishing, 2019.
8. Fan, Bowen, Yongjun Men, Susan AP van Rossum, Guotai Li, and RienkEelkema. "A Fuel□Driven Chemical Reaction Network Based on Conjugate Addition and Elimination Chemistry." ChemSystemsChem 2, no. 1 (2020): e1900028.
9. Xhafa, Fatos, SrikantaPatnaik, and MadjidTavana, eds. Advances in Intelligent Systems and Interactive Applications: Proceedings of the 4th International Conference on Intelligent, Interactive Systems and Applications (IISA2019). Vol. 1084. Springer Nature, 2019.
10. Kakulavaram, S. R. (2024). "Intelligent Healthcare Decisions Leveraging WASPAS for Transparent AI Applications" Journal of Business Intelligence and DataAnalytics, vol. 1 no. 1, pp. 1–7. doi: https://dx.doi.org/10.55124/csdb.v1i1.261
11. Suvalova, T., O. Suvalov, and E. Kashtanova. "Digital transformation of HR technologies." In XXIII International Conference" Culture, Personality, Society in the Conditions of Digitalization: Methodology and Experience of Empirical Research Conference".—Ekaterinburg, 2020, pp. 191-199. Knowledge E, 2021.
12. Prasad, Thejas. "Cloud Enterprise Resource Planning Software Design for Healthcare Account Receivables Billing &CashTransactions." North American Journal of Engineering Research 2, no. 1 (2021).
13. Cheruiyot, Koech Charles, and RatemoMakiya Cyprian. "Integrated Financial Management Information System in County Treasuries in Kenya: Empirical Analysis of the Implementation." (2023).
14. Franklin, James L. "Direct expansion solar collector-heat pump system." U.S. Patent 4,798,056, issued January 17, 1989.
15. PK Kanumarlapudi. "Improving Data Market Implementation Using Gray Relational Analysis in Decentralized Environments" Journal of Artificial intelligence and Machine Learning., 2024, vol. 2, no. 1, pp.

1–7. doi: https://dx.doi.org/10.55124/ jaim.v2i1.271

16. Kim, Hye Jin, Hyung Sun Kim, Jae Myun Lee, Sang Sun Yoon, and Dongeun Yong. "Rapid detection of Pseudomonas aeruginosa and Acinetobacterbaumannii Harboring bla (VIM-2), bla (IMP-1) and bla (OXA-23) genes by using loop-mediated isothermal amplification methods." Annals of laboratory medicine 36, no. 1 (2016): 15-22.

17. Schiller, Stefan, and Ignace De Beelde. Disclosure of improvement activities related to tangible assets. FaculteitEconomie en Bedrijfskunde, Univ. Gent, 2003.

18. Zakharkina, Liudmyla, PavloRubanov, BalshekerAlibekova, OleksiiZakharkin, and LuizaMoldashbayeva. "The impact of digital transformation in the accounting system of fuel and energy complex enterprises (International Experience)." International Journal of Energy Economics and Policy 12, no. 5 (2022): 152-161.

19. Peram, S. R. (2024). Automated Label Detection and Recommendation System Using Deep Convolution Neural Networks and SPSS-Based Evaluation. International Journal of Computer Science and Data Engineering, 1(2), 258. https://doi.org/10.55124/csdb.v1i2.258

20. Sciancalepore, Vincenzo, FaqirZarrarYousaf, and Xavier Costa-Perez. "Z-TORCH: An automated NFV orchestration and monitoring solution." IEEE Transactions on Network and Service Management 15, no. 4 (2018): 1292-1306.

21. Calderaro, Adriana, MirkoButtrini, MaddalenaPiergianni, Sara Montecchini, Monica Martinelli, Silvia Covan, Giovanna Piccolo et al. "Evaluation of a modified meropenem hydrolysis assay on a large cohort of KPC and VIM carbapenemase-producing Enterobacteriaceae." PLoS One 12, no. 4 (2017): e0174908.

22. Quandt, Richard E. "Tests of the hypothesis that a linear regression system obeys two separate regimes." Journal of the American statistical Association 55, no. 290 (1960): 324-330.

23. Andrews, David F. "A robust method for multiple linear regression." Technometrics 16, no. 4 (1974): 523-531.

24. Kavitha, S., S. Varuna, and R. Ramya. "A comparative analysis on linear regression and support vector regression." In 2016 online international conference on green engineering and technologies (IC-GET), pp. 1-5. IEEE, 2016.

25. Andrews, David F. "A robust method for multiple linear regression." Technometrics 16, no. 4 (1974): 523-531.

26. Kavitha, S., S. Varuna, and R. Ramya. "A comparative analysis on linear regression and support vector regression." In 2016 online international conference on green engineering and technologies (IC-GET), pp. 1-5. IEEE, 2016.

27. Al-Anazi, AmmalFannoush, and Ian Donald Gates. "Support vector regression for porosity prediction in a heterogeneous reservoir: A comparative study." Computers & Geosciences 36, no. 12 (2010): 1494-1503.

28. Khan, Faisal M., and Valentina Bayer Zubek. "Support vector regression for censored data (SVRc): a novel tool for survival analysis." In 2008 Eighth IEEE International Conference on Data Mining, pp. 863-868. IEEE, 2008.

29. Al-Anazi, AmmalFannoush, and Ian Donald Gates. "Support vector regression for porosity prediction in a heterogeneous reservoir: A comparative study." Computers & Geosciences 36, no. 12 (2010): 1494-1503.

30. Khan, Faisal M., and Valentina Bayer Zubek. "Support vector regression for censored data (SVRc): a novel tool for survival analysis." In 2008 Eighth IEEE International Conference on Data Mining, pp. 863-868. IEEE, 2008.