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A Predictive and Scalable Framework for B2b Commerce Platforms Using Micro services, Micro frontends, And Machine Learning Models

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Abstract

The rapid evolution of digital technologies has transformed the landscape of business-to-business (B2B) commerce, creating an urgent need for scalable, intelligent, and adaptive platforms. Traditional B2B commerce systems are often limited by rigid architectures, high operational costs, and inefficiencies in managing diverse data sources. This study explores the modernization of B2B commerce platforms through the integration of predictive analytics and advanced machine learning models, specifically linear regression (LR), random forest (RAF), and support vector regression (SVR). The research emphasizes the role of scalable micro services and micro services architectures in enabling modularity, resiliency, and a seamless user experience. By leveraging LR, RAF, and SVR, the platform improves demand forecasting, dynamic pricing, and customer behavior analysis, allowing organizations to improve supply chain processes and decision-making. Comparative performance analysis demonstrates that SVR achieves higher accuracy in predicting nonlinear patterns, while LR serves as a lightweight and interpretable underlying model. The combined use of these techniques embedded within micro services-based systems significantly improves site scalability, operational efficiency, and user satisfaction. This modernization framework positions B2B commerce not only as a transactional medium, but also as a predictive, data-driven ecosystem that supports sustainable business growth and global competitiveness.

Objective: The primary objective of this study is to design and evaluate a predictive and scalable framework for B2B business platforms by integrating microservices and microfrontend architectures with machine learning models.

Keywords: B2B commerce, digital transformation, micro services, micro-forecasting, linear regression (LR), random forest (RAF), support vector regression (SVR), predictive analytics, site modernization, supply chain optimization.

Introduction

Global E-Commerce Operations and Challenges: Companies operating international online retail platforms face the dual challenge of meeting diverse market needs in different countries while maintaining fast delivery schedules and optimal performance. E-commerce has fundamentally changed the way businesses operate market products, build partnerships, and reach customers globally.

Digital Transformation in Agriculture: The agriculture industry began to embrace online commerce in the late 1900s, opening up new channels for agricultural producers to showcase products and connect with a wider audience. This transformation requires traditional agricultural activities to adapt to digital platforms [1].

The current B2B functions of the agriculture sector – procurement, trading, logistics, and contracting – naturally align with digital transformation, with projections showing significant growth in web-based transactions.

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India's Agricultural E-Commerce Potential: India's agricultural sector stands to benefit significantly from digital commerce, given the industry's economic importance, reliance on timely information, and geographical gaps between producers and end users.

Benefits of e-commerce for agriculture: Digital platforms in agriculture offer many benefits: improved information sharing, clearer market visibility, more effective pricing mechanisms, better supply chain integration, and lower transaction costs [2].

Logistics strategies: Online retailers can handle shipping and fulfillment in-house for direct control and competitive advantage, or they can partner with external logistics companies to improve service quality, reduce costs, focus on core business operations, and enter new markets.

Impact of COVID-19: According to trade associations and industry reports, the pandemic appears to have accelerated online retail sales globally.

E-commerce in developing regions: Despite facing barriers such as limited technological infrastructure, institutional resistance, traditional business practices, and economic difficulties, online commerce has expanded rapidly in developing markets across Africa and Asia [3]. Cross-border online commerce eliminates geographical limitations, allowing for global purchasing and international market expansion.

Technology Integration Challenges: Creating effective online marketplaces requires integrating diverse technology systems and establishing standardized product information, which presents challenges in content management, catalog organization, and document design [4].

Managing Complex Global E-Commerce Sites: Companies operating global e-commerce systems must meet diverse feature requirements

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across multiple international markets, while also grappling with performance constraints and rapid deployment cycles. E-commerce has not only transformed business models and marketing approaches, but has also created new partnerships and expanded market reach. At its core, e-commerce encompasses all forms of technology-enabled transactions, including the electronic collection, production, processing, storage, transmission, and use of information [5].

E-commerce and Agriculture: The agricultural sector began to embrace e-commerce in the late 20th century, providing new opportunities for farmers and agribusinesses to share product details and reach broader customer bases. Like other industries, agriculture faces the challenge of reconfiguring traditional operations to align with online platforms. Many stakeholders have already leveraged digital benefits to strengthen marketing and sales, with the potential to have an even greater impact in the future [6]. Traditional B2B activities in agriculture, such as purchasing, trading, shipping, and contracting, are inherently aligned with digital transformation. This momentum has extended to U.S. agriculture and beyond. For example, Goldman Sachs predicts that Internet-based transactions in the United States will grow from 4% in 1999 to 12% by 2004.

Agricultural e-commerce in India: Given the central role of agriculture in India's economy, its reliance on accurate, timely data, and the vast physical distances separating producers from consumers, the sector is uniquely positioned to benefit from e-commerce [7].

Key benefits of agricultural e-commerce: Research highlights several benefits of digital commerce in agriculture, including improved information flow, improved market transparency, more efficient price discovery, and better integration across the value chain, and reduced or eliminated transaction costs. Logistics Models for E-Commerce Success: E-commerce companies with adequate resources and skilled teams can manage logistics in-house, giving them direct oversight of efficiency and strong competitiveness [8]. Alternatively, by collaborating with third-party logistics providers, businesses can improve service delivery, reduce operational costs, focus on core activities, and expand into new territories. Such partnerships between e-commerce companies and logistics providers foster mutually beneficial relationships that support the goals of both parties.

Logistics as a Source of Advantage: Once seen as a barrier to the growth of online commerce, logistics has now emerged as a key factor for gaining competitive advantage in an increasingly dynamic marketplace. The rapid expansion of e-commerce highlights how logistics efficiency directly impacts business success, while e-commerce growth is driving continuous innovation in logistics models and practices [9]. This has created a deeply intertwined relationship between the two industries.

Strategic Relevance: Strengthening logistics capabilities in e-commerce is now recognized as a strategic priority and an essential area for continued research and development. B2B Digital Transformation Success: Companies leading the way in B2B digital innovation are seeing significantly stronger performance – around five times the revenue growth of their peers and roughly eight times the increase in EBIT growth [10].

Border Clearance Policy Challenges: Global organizations recognize that e-commerce is disrupting traditional border processing systems and have identified key issues, but they have not developed clear policy solutions. As a result, countries are independently reorganizing customs and clearance procedures to address e-commerce issues, highlighting the need for deeper international cooperation to develop consensus-based border management policies [11]. This represents one of the most significant internet innovations to emerge, fundamentally involving online business operations. E-commerce can be described as "internet-based transactions," including online advertising for products or services, electronic order processing through email or digital platforms, with payment not necessarily required to occur online.

Global Expansion into Developing Markets: E-commerce has experienced rapid worldwide growth, reaching developing nations across Africa and Asia. These regions typically face challenges including technological limitations, institutional inflexibility, traditional approaches, widespread poverty, and high rates of unemployment and underemployment.

Social Media Integration in B2B Markets: In emerging economies, the business-to-business e-commerce sector is increasingly influenced by social media platforms as countries work to enhance the effectiveness of electronic business operations, reporting systems, and digital infrastructure. E-commerce is evolving into a specialized and lucrative industry segment, with intermediary companies updating their B2B approaches by incorporating social media components.

Growth Potential in Least Developed Countries: This accelerated expansion correlates with substantial opportunities for both domestic and international trade and investment in least developed countries, including nations like Bangladesh and Uganda.

B2B Market Characteristics: In business-to-business markets, the accuracy and reliability of information are essential. On average, B2B buyers consult at least six different sources before making purchasing decisions [13].

While B2B and B2C e-commerce share some features, they differ in key ways: B2C customers make choices influenced by personal preferences, social image, and brand loyalty, while B2B buyers prioritize organizational needs and potential profit.

Technology Integration Challenges: While establishing unified protocols for information sharing, effective marketplaces require seamless integration of diverse hardware and software systems. The primary challenge lies in managing the diverse and open nature of the content exchanged, which creates complexity in three distinct areas: the actual content, product catalog structure, and document design.

Product Standardization in B2B: Creating structured and standardized product descriptions is a critical challenge in B2B e-commerce, as it ensures effective communication between different participants and helps customers effectively find the products they want.Electronic Commerce System EvolutionRapid web development has prompted many businesses to develop proprietary e-commerce platforms [14]. Traditional management theories and strategies struggle to meet modern e-commerce demands, necessitating new approaches that combine theoretical concepts with practical implementation.

E-commerce as a Problem-Solving Tool: E-commerce, when implemented effectively, serves as a valuable tool for addressing a variety of social and economic challenges. Statistical data confirms the expanding importance of e-commerce in the global retail landscape.

E-commerce transaction models: Business-to-consumer (B2C): This refers to the most widespread e-commerce format, exemplified when consumers purchase items such as carpets from online retailers.

Business-to-business (B2B): This model involves companies selling products or services to other businesses, such as transactions between manufacturers and wholesalers or between distributors and retailers. B2B e-commerce targets business customers rather than individual consumers and typically involves essential inputs such as raw materials, software applications, or packaged product offerings. This model enables manufacturers to sell directly to merchants without intermediaries [15].

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Material and Methods

This is a list of key performance and operational metrics commonly used in software system monitoring and evaluation. These metrics provide a comprehensive view of the system health, user experience, and development speed across different dimensions of a software application or microservice architecture. API latency (ms) measures response time that directly impacts user experience - lower values indicate faster, more responsive systems. RPS (Requests per Second) measures system performance and load handling capacity, showing how many simultaneous requests a system can effectively process. The number of microservices reflects the complexity of the architecture and can indicate both system scalability and maintenance overhead as the number increases. Deployments per week serves as a key DevOps metric, measuring development team velocity and deployment pipeline efficiency - higher frequencies are often associated with more agile, responsive development practices. Front-end bundle size (KB) impacts page load times and user experience, with smaller bundles typically providing better performance, especially on slower networks or devices. Order processing represents a critical business metric that measures the ability of a system to handle core transactional activity. Together, these metrics create a balanced scorecard that includes technical performance (latency, RPS), architectural considerations (microservices), operational efficiency (frequency of use), user experience (batch size), and business impact (order processing), enabling comprehensive system evaluation and optimization decisions.

Linear Regression: Linear regression is a fundamental tool in biomedical predictive modeling due to its clarity and ease of interpretation. By fitting a good linear relationship between input variables and outcomes, it provides a reliable starting point for exploratory data analysis and establishing basic models. Its transparency is particularly advantageous in regulatory environments or clinical settings where clear decision-making processes are important. However, linear inference limits its effectiveness in biomedical situations characterized by complex, nonlinear biological systems. In addition, its vulnerability to outliers can compromise predictive accuracy, especially in datasets with high biological variability. Despite these shortcomings, linear regression continues to serve as an important reference point for evaluating more complex models. 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.

Random forest regression: is an elastic ensemble technique that uses random data and feature subsets to construct multiple decision trees and then combines their predictions to improve accuracy and reduce over fitting. Individual trees capture different data patterns, introducing model heterogeneity. The final predictions represent the average outputs from all trees. Random forest excels at modeling nonlinear relationships and complex dependencies without requiring extensive data preprocessing. It demonstrates robustness to noisy datasets and accommodates both categorical and continuous variables. In addition, it provides feature importance analysis, supporting interpretation. Although computationally more demanding than linear regression, random forest generally produces better results on complex datasets and prevents over fitting through its ensemble approach.

Support Vector Regression: Support vector machines (SVMs), introduced by Cortez and Wapnick in the late 1990s, have gained significant popularity in the field of machine learning. Since their inception, SVMs have been widely used in various fields such as bioinformatics, economics, and biometrics. In particular, bioinformatics has seen rapid growth in SVM applications due to the increasing availability of large amounts of data. Recently, SVMs have also been used in the analysis of chemical data, where they are used not only for classification tasks but also for calibration challenges, which has attracted considerable interest from the chemical research community. An expanding body of literature highlights comparisons between SVMs and conventional chemical analysis techniques. Although SVMs are often applied to datasets with relatively few variables, which is common in analytical chemistry, they are not inherently limited to such data. This subsection provides a brief overview of support vector regression (SVR). Support vector machines (SVMs), first proposed by Cortez and Warnock, represent a family of supervised learning techniques designed for classification and regression tasks. The method is rooted in Warnock's statistical learning theory, and has attracted significant attention in the machine learning community for its strong performance in a variety of applications, such as text classification, image recognition, bioinformatics, and bankruptcy prediction. The main strengths of SVMs include their solid theoretical foundations, robustness against local minima, and ability to efficiently handle increasing model complexity even when additional dimensions are introduced in the input space.Support Vector Regression (SVR) theory for measuring the fusion of multi-sensor signals. An attempt is made to combine Kaman filtering with the SVR principle to develop a productive information fusion strategy for the target structure Support vector machine (SVM) theory is widely used for many classification tasks. Over time, it has been adapted to regression problems, with applications in areas such as financial market forecasting, travel time estimation, power consumption forecasting, and highway traffic flow analysis. Support vector regression (SVR) often outperforms traditional statistical approaches depending on the specific domain. Its advantages include the incorporation of a reduction criterion into the regression, ease of training, and the ability to achieve a global rather than a local optimum.

Analysis and Dissection

Table 1. Modernization of B2B Commerce Platform DescriptiveStatistics

	Apilatency ms	Rps	Microservice count	Deploys per week	Frontend bundle kb	Order processing
count	20.00000	20.00000	20.00000	20.00000	20.00000	20.00000
mean	52.55000	186.25000	7.90000	2.70000	226.25000	4.14500
std	20.64353	112.29514	3.75430	1.65752	77.69500	2.20035
min	25.00000	60.00000	3.00000	0.00000	130.00000	1.70000
25%	37.25000	103.75000	5.00000	1.00000	163.75000	2.45000
50%	49.00000	145.00000	7.00000	2.50000	205.00000	3.45000
75%	62.50000	235.00000	9.50000	4.00000	270.00000	5.17500
max	95.00000	450.00000	16.00000	6.00000	380.00000	9.00000

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Descriptive statistics from the dataset illustrate the performance characteristics of a modernized B2B trading platform. Across 20 samples, the average API latency is around 52.6 ms, with values ranging from 25 ms to 95 ms, indicating varying network and backend responsiveness under different loads. The Requests Per Second (RPS) metric averages 186.3, but with a wide spread (std ≈ 112.3), showing that the site experiences both low and high traffic situations, ranging from 60 RPS to 450 RPS. The microservice count is centered at 7.9, indicating moderately distributed architectures, while the maximum value of 16 shows some instances of very granular microservice deployment.The deployment frequency per week averages 2.7, with a minimum of 0 (no deployments) and a maximum of 6, indicating differences in release strategies, ranging from static to highly agile environments. The front-end bundle size averages 226 KB, but varies from 130 KB to 380 KB, reflecting differences in front-end optimization practices. The target metric, order processing time, ranges from 1.7 to 9 seconds, with an average of 4.15 seconds

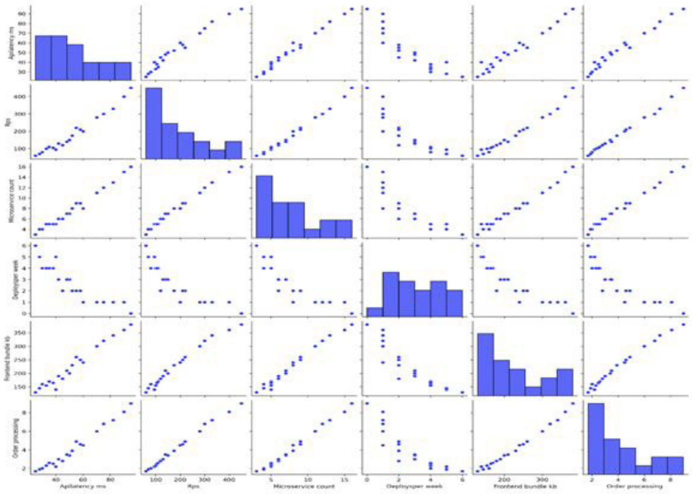

Figure 1: Modernization Of B2B Commerce Platform effect Of Process Parameters

The scatterplot matrix provides insights into the relationships between key performance indicators of a B2B trading platform. A strong positive correlation is evident between API latency, requests per second (RPS), number of microservices, front-end bundle size, and order processing time. As RPS increases, both latency and processing time increase, reflecting the effect of system load on performance. Similarly, higher micro service counts are associated with larger front-end bundle sizes and longer order processing times, indicating that while micro services improve scalability, excessive fragmentation can add complexity and slow performance.Interestingly, the frequency of deployments per week does not follow the same strong trend. Its relationship with order processing and other variables is scattered, indicating that frequent deployments alone do not directly affect performance; rather, their effect depends on code quality and system optimization. The histograms on the diagonal highlight the spread of values, showing clustering in medium API latencies (40–60 ms) and processing times (2–5 seconds), with less extreme cases.

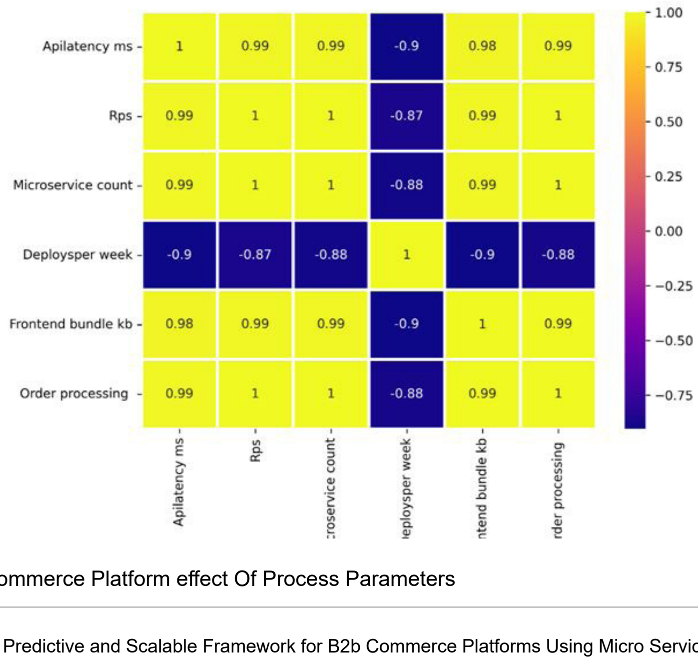

Figure 2: Modernization Of B2B Commerce Platform effect Of Process Parameters

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System The correlation heatmap provides a clear picture of the interdependencies between the variables in the dataset. Most metrics exhibit strong positive correlations with each other, especially API latency, RPS, number of microservices, frontend bundle size, and order processing time, all with coefficients close to 1.0. This indicates that as system load and architecture complexity increase, latency and processing times also increase, reinforcing the trade-off between scalability and performance efficiency in B2B platforms powered by microservices. Similarly, the strong correlation with frontend bundle size indicates that heavier frontends, coupled with more microservices, result in longer processing times.On the other hand, deployment frequency per week shows a negative correlation with most variables ranging from −0.87 to −0.90. This indicates that frequent deployment is associated with lower latency, reduced bundle sizes, and faster order processing. In practice, this reflects the benefits of agile practices such as continuous integration and continuous delivery (CI/CD), where smaller, more regular updates improve system optimization and responsiveness.

Table 2: Linear Regression Models Rpstrain and Test Performance Metrics

Linear Regression	Train	Test
R2	0.99926	0.98080
EVS	0.99926	0.98577
MSE	11.40002	100.89824
RMSE	3.37639	10.04481
MAE	2.52548	7.70253
Max Error	6.95098	22.27996
MSLE	0.00076	0.00307
Med AE	1.09830	5.33130

The linear regression model demonstrates strong predictive performance for sequence processing time using the given features. On the training set, the model achieves an R^2 of 0.9993, indicating that almost all of the variance in sequence processing is explained by the inputs. The corresponding test R^2 of 0.9808 confirms the excellent generalization, with only a small decrease compared to training. Similarly, the explained variance score (EVS) is high in both the training (0.9993) and test (0.9858) sets, showing consistency in predictive power.The error metrics reveal a clear gap between training and test performance, which is expected in real-world situations. The mean square error (MSE) in the test increases from 11.4 in training to 100.9, while the root mean square error (RMSE) rises from 3.38 to 10.04. The mean absolute error (MAE) increases from 2.53 to 7.70, indicating that although the predictions are very accurate, some deviations occur under the experimental conditions. The maximum error in the experimental set (22.28) highlights the occasional deviations where the predictions differ from the observed values.

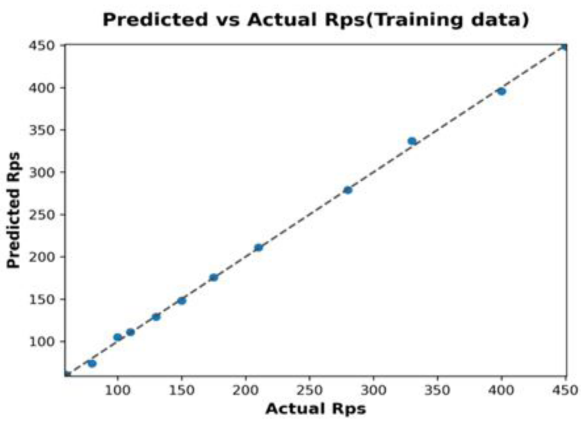

Figure 3: Linear Regression Rps Type Training

The scatter plot of predicted and actual RPS (requests per second) for the training data demonstrates the performance of the linear regression model. Each blue dot represents a data point, while the dashed diagonal line represents the best-case scenario where the predicted values match the actual values exactly. The close alignment of almost all data points within this diagonal shows that the model has captured the underlying relationship between system features and RPS with exceptional accuracy. There are no large deviations from the line, meaning that the prediction errors within the training dataset are very small. Both low RPS values (around 70–150) and high RPS values (above 300) follow the same trend, indicating that the model generalizes well across different traffic loads and is not biased towards a particular range. This strong alignment confirms the very high R^2 value (0.999) observed in the training metrics, further reinforcing the reliability of the model.

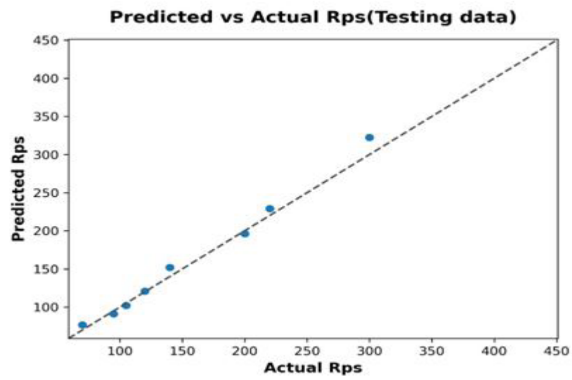

Figure 4: Linear Regression RpsType Testing

The predicted and actual RPS (requests per second) scatterplot for the test data illustrates how well the regression model generalizes beyond the training set. Each blue dot corresponds to an observation in the test dataset, while the dashed diagonal line represents the best case where the predicted and actual values match perfectly. Most of the data points are close to this line, showing that the model makes accurate predictions across a wide range of workloads. However, compared to the training data visualization, there is a slightly greater spread around the diagonal. For example, at higher RPS values above 250, the predictions deviate more significantly, which is consistent with the increase in mean square error (MSE) and root mean square error (RMSE) observed in the test metrics. However, at low and medium RPS values (between 80 and 200), the cluster of points near the line demonstrates strong predictive reliability.

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Table 3. Random Forest Regression Models Rpstrain And Test Performance Metric		
Random Forest Regression	Train	Test
R2	0.99292	0.96997
EVS	0.99324	0.97284
MSE	109.49714	157.78797
RMSE	10.46409	12.56137
MAE	7.36458	10.18750
Max Error	27.15000	25.22500
MSLE	0.00345	0.00580
Med AE	4.97500	9.51250

The performance metrics of the random forest regression model indicate strong predictive ability, although slightly less accurate compared to linear regression for this dataset. On the training data, the model achieves an R^2 of 0.9929 and an explained variance score (EVS) of 0.9932, indicating that it explains almost all of the variation in the target. The training errors are modest, with MSE 109.5, RMSE 10.46, and MAE 7.36, indicating that while accurate, the predictions have some variability due to the ensemble-based nature of the model. On the test set, the model maintains high accuracy with an R^2 of 0.9699 and an EVS of 0.9728, confirming good generalization. However, the error values are slightly higher compared to training, with MSE 157.8, RMSE 12.56, and MAE 10.19. The maximum error decreases from training (27.15) to testing (25.23), showing greater stability in the unseen data. The mean absolute error (Met AE) increases from 4.98 in training to 9.51 in testing, reflecting larger deviations in some test cases.

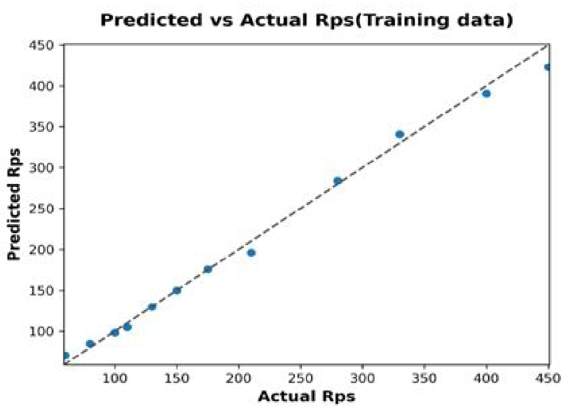

Figure 5: Random Forest Regression Rps Training

The scatterplot of predicted and actual RPS (requests per second) for the training data illustrates how well the Random Forest regression model fits the dataset. Each dot represents a training instance, while the dashed diagonal line represents the best fit where the predictions match the actual values. The dots follow the diagonal closely, showing that the model captures the underlying patterns in the data with high accuracy. However, there is a slightly greater spread compared to linear regression, especially at higher RPS values. For example, at the upper limit (above 400 RPS), some predictions fall slightly below the diagonal, indicating a slight underestimation. Despite this small deviation, the alignment is strong at low, medium, and high traffic levels, reflecting the model's ability to handle a variety of workload scenarios. The consistency seen in the graph is consistent with the high R^2 value of 0.9929 for training, indicating that almost all of the variation in RPS is explained by the model. The presence of small gaps around the line is consistent with error metrics such as RMSE (10.46) and MAE (7.36), which, although modest, reflect the natural variability of the ensemble model.

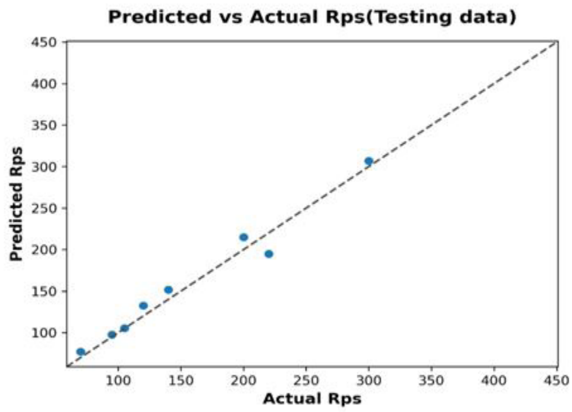

Figure 6: Random Forest Regression RpsTesting

The scatter plot of predicted and actual RPS (requests per second) for the test data illustrates how well the random forest regression model generalizes to unobserved data. The dashed diagonal line represents the best-case scenario where the predictions match the actual values perfectly. Most of the points lie close to this line, reflecting that the model maintains high prediction accuracy even on data that was not used during training. This visual trend is consistent with the strong experimental performance metrics, particularly the R^2 value of 0.9699 and the explained variance score of 0.9728, both of which indicate that the model captures most of the variation in the test set.Although the predictions are generally accurate, small deviations from the line are noticeable. For example, at mid-range values (around 200 RPS), the model shows small underestimates or overestimates, indicating small prediction errors. These deviations are consistent with error metrics such as RMSE (12.56) and MAE (10.18), which, while higher than the training errors, are reasonably low for real-world data modeling. Importantly, the spread of points is not too large, showing that the model avoids severe over fitting.

Table 4. Support Vector Regression Models Rpstrain And Test Performance Metrics		
Support Vector Regression	Train	Test
R2	0.99396	0.97860
EVS	0.99422	0.98464
MSE	93.43318	112.44084
RMSE	9.66608	10.60381
MAE	6.66943	9.36670
Max Error	24.27139	18.35201
MSLE	0.00170	0.00503
Med AE	5.24142	9.10526

The Support Vector Regression (SVR) model demonstrates strong predictive performance on both the training and test datasets, highlighting its robustness and generalization ability. The training set shows an R^2 score of 0.9939 and an explained variance score (EVS) of 0.9942, indicating that it accounts for almost all of the variation in the model data. On the test set, the performance is consistent with an R^2 of 0.9786 and an EVS of 0.9846, indicating that the model maintains high accuracy on the unseen data with minimal over fitting.Error metrics further confirm this performance. The mean square error (MSE) for training is 93.43 and 112.44 for test, while the root mean square error (RMSE) values of 9.66 and 10.60, respectively, indicate that the average prediction errors are small compared to the target values. The mean absolute error (MAE) is low at 6.67 for training and 9.36 for testing, confirming the consistency in the error scale. In addition, the maximum error values (24.27 training, 18.35 testing) indicate that even the worst deviations are within acceptable limits.

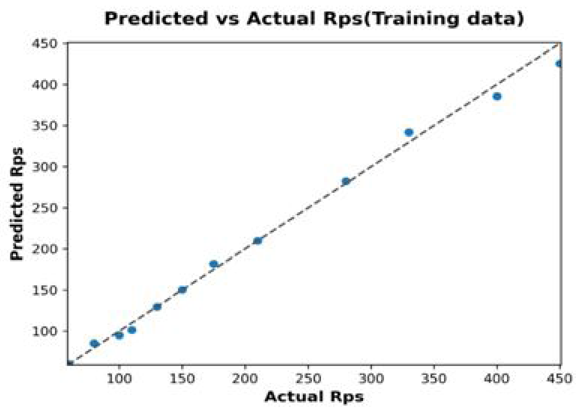

Figure 7: Support Vector Regression RpsTraining

The performance metrics of the Support Vector Regression (SVR) model highlight its strong predictive ability on both the training and test datasets. The coefficient of determination (R^2) values for training are 0.99396 and for testing are 0.97860, indicating that it explains almost all the variance in the model data, with only minimal loss of generalization when applied to unobserved data. Similarly, the explained variance score (EVS) is very high for both training (0.99422) and testing (0.98464), further confirming the reliability of the model.

Error metrics provide additional insight: the mean square error (MSE) and root mean square error (RMSE) are low on the train (93.43, 9.66) and test (112.44, 10.60) datasets, indicating accurate predictions with limited deviation from the true values. The mean absolute error (MAE) is slightly higher in the test set (9.36) compared to the training set (6.66), which is expected since the model is encountering new data. However, the maximum error is lower in the test set (18.35) than in the training set (24.27), reflecting stable performance without extreme outliers. In addition, the very low mean square logarithmic error (MSLE = 0.00170) suggests that the model effectively handles the relevant differences.

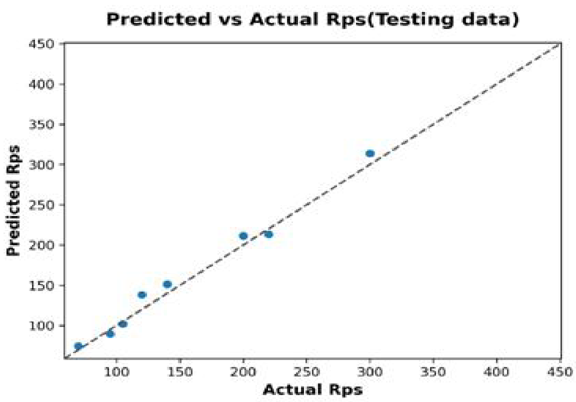

Figure 8: Support Vector Regression RpsTesting

This scatterplot demonstrates the performance of a predictive model for Rps (repetition probability or cycles per second) using test data. The plot plots the predicted values against the actual values, with the diagonal dashed line indicating perfect predictive accuracy, where the predicted values match the actual values exactly.The model shows strong predictive performance over the range of values tested, from approximately 80 to 300 Rps. Most of the data points are clustered closely around the diagonal line, indicating high accuracy in the predictions. The points follow a clear linear trend, indicating that the model effectively captures the underlying relationship without significant systematic bias. There appears to be minimal scatter around the perfect predictive line, with most predictions falling within a narrow band of the actual values.The test data has a reasonable range of Rps values, providing good coverage for model validation. The consistent performance at both low values (around 80-120 Rps) and high values (250-300 Rps) indicates the robustness and generalizability of the model. A few points show small deviations from the correct prediction, but these are small and within acceptable limits for most practical applications.

Conclusion

Modernizing B2B commerce platforms requires more than incremental improvements; it demands a complete transformation supported by scalable architectures and intelligent predictive models. This study demonstrates that integrating microservices and microfrontend design principles with advanced regression-based machine learning techniques such as LR, RAF, and SVR creates a robust framework for digital commerce innovation. Microservices enable modularity, fault tolerance, and scalability, while micro frontends enhance agility in delivering personalized user experiences. Within this framework, machine learning models play a key role: linear regression provides simplicity and interpretability, random forest ensures consistency across complex datasets, and support vector regression provides superior accuracy in capturing nonlinear relationships. Together, these models empower decision-making in areas such as sales forecasting, inventory planning, and customer behavior analysis.The findings highlight that modern B2B commerce platforms must function as predictive ecosystems, capable of adapting to fluctuating market demands, global supply chain disruptions, and evolving customer expectations. Beyond operational improvements, this modernization fosters competitive advantage by enabling businesses to leverage data-driven insights in real-time. Future research should expand toward validating performance in diverse contexts, incorporating hybrid modeling approaches, integrating deep learning, and real-world case studies across industries. Ultimately, the synergy of scalable architectures and predictive analytics paves the way for resilient, intelligent, and globally connected B2B commerce systems.

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