SciForce

Journal of Business Management and Entrepreneurship

Journal homepage: www.sciforce.org

ISSN : 2831-4131

Open Access Research Article

Machine Learning-Driven Reliability Engineering for E-Commerce Sites: A Study on Browsing, Cart, and Checkout Phases

Divya Soundarapandian

Software Engineering Manager, The Home Depot., United States

Abstract

This study explores reliability engineering in e-commerce systems by analyzing critical user journey stages – browsing, cart, and checkout – using advanced machine learning models. The research uses random forest regression (RFR) and support vector regression (SVR) to assess and predict system performance, stability, and potential failure points. Data was obtained from simulated e-commerce transactions that included key parameters such as response time, server load, transaction success rate, and error frequency. The models were evaluated using statistical indicators including coefficient of determination (R^2), mean square error (MSE), and mean absolute error (MAE) to measure predictive accuracy. The results indicated that both models achieved high reliability and accuracy, with SVR showing slightly higher generalization ability. The findings highlight that predictive modeling can effectively identify performance bottlenecks, reduce downtime, and improve the overall robustness of e-commerce operations. By integrating reliability engineering principles with machine learning techniques, this study contributes to improving user experience, enhancing system resilience, and ensuring scalable and stable online transaction environments. This hybrid analytics approach provides a foundation for developing proactive monitoring strategies in modern e-commerce infrastructures.

Keywords: Reliability Engineering, E-Commerce, Random Forest Regression, Support Vector Regression, Performance Optimization

Objective: Improve the reliability and efficiency of the browsing, cart, and checkout processes, ensuring a seamless and consistent e-commerce user experience

Introduction

The rapid advancement of e-commerce has transformed online shopping carts from simple tools used to track purchase statuses into complex, mission-critical systems that form the foundation of digital commerce. These modern systems must effectively integrate complex interactions across a wide range of devices, browsers, and user profiles while maintaining exceptional performance, security, and reliability. However, the rapid nature of e-commerce growth, often described as progressing in "web years," introduces significant challenges in ensuring consistent system reliability [1]. Reliability engineering in e-commerce primarily focuses on three.

Interdependent stages: browsing, cart, and checkout. Each stage poses its own reliability demands. Browsing generates a high volume of high-frequency database queries, shopping carts involve medium-intensity read/write operations that must maintain transaction integrity, and the checkout stage securely integrates with external payment gateways and validation systems. Failures at any of these stages can lead to immediate revenue loss, reputation damage, and diminished customer trust [2]. This study examines the application of reliability engineering principles to e-commerce shopping cart systems, drawing on extensive research and analysis of failure modes. The goal is to develop systematic methods for detecting, describing, and mitigating failures that threaten system reliability across the browse–cart–checkout continuum.

By identifying common failure points, ranging from server crashes and memory leaks to capacity limitations and operational errors, engineering teams can implement more resilient, risk-based testing and design strategies that maintain reliable e-commerce performance even under high demand [3]. The checkout process represents a critical point of interaction between technical reliability and human cognitive processes. It directly impacts conversion rates, customer satisfaction, and business success. While system failures such as database outages or capacity planning failures can compromise the technical reliability of online transactions, human factors are equally detrimental. Research shows that high cart abandonment rates often stem not only from technical issues, but also from cognitive mismatches between the way users process information and the structure of checkout interfaces [4].

To address this, e-commerce trustworthiness must be approached from two complementary dimensions: technical trustworthiness, which ensures that distributed systems with multiple servers, databases, and payment gateways operate seamlessly; and cognitive trustworthiness, which focuses on user interaction and experience at the browsing, cart, and checkout stages. Empirical studies indicate that individual cognitive processing styles—particularly those aligned with the Wholist/Analyst dimension—significantly influence how users perceive and complete online transactions [5]. Wholist users prefer structured, guided, and sequential processes that present information in manageable steps. This discrepancy highlights the importance

Received date: July 15, 2024 **Accepted date:** July 24, 2024; **Published date:** August 3, 2024

Corresponding Author: Divya Soundarapandian, Software Engineering Manager, The Home Depot., United States; E- mail: divyasoundarapandian90@gmail.com

Citation: Divya Soundarapandian (2024). Machine Learning-Driven Reliability Engineering for E-Commerce Sites: A Study on Browsing, Cart, and Checkout Phases. Journal of Business Management and Entrepreneurship, 3(1), 1-9. doi: https://doi.org/10.55124/jbme.v3i1.239

of cognitive alignment in interface design. If its design conflicts with their natural cognitive tendencies, even a technically flawless system can fail in the eyes of the user [6]. Modern reliability engineering in e-commerce requires combining robust system design with cognitively compatible interfaces to ensure both technical uptime and user success. Achieving this balance requires combining system performance optimization with psychological insights from human-computer interaction research [7]. The e-commerce ecosystem is one of the most dynamic and demanding technological environments, where reliability represents not just a system metric but also a key business requirement.

At the heart of this ecosystem is the browse-cart-checkout continuum, a seemingly simple process that hides enormous technical and cognitive complexity. This three-step flow, handling billions of transactions annually across diverse networks, platforms, and user populations, generates the majority of online revenue. Any disruption, whether technical or empirical, directly results in lost revenue, diminished trust, and reputational damage [8]. Technically, e-commerce sites must manage decentralized architectures that integrate interactions between web servers, databases, caches, payment processors, and external APIs, often spread across multiple regions. While a shopping cart may seem straightforward to users, it is actually a complex state management system responsible for maintaining session persistence, handling simultaneous access from thousands of shoppers, dynamically scaling to accommodate traffic spikes, and integrating with inventory and order management systems [9]. Research on system failures identifies recurring issues such as inaccessible catalogs due to database errors, gradual performance degradation from memory leaks, inadequate capacity planning that leads to outages during peak periods, and software updates that introduce new vulnerabilities.

The decentralized nature of these systems increases risk by multiplying the potential points of failure that can be spread across components. A small mis configuration in one region can prevent order fulfillment worldwide, while an outdated cache can create inconsistent pricing that confuses customers. Similarly, interruptions from third-party payment gateways can leave users uncertain about whether their purchase was successful [11]. Traditional reliability engineering techniques, including failure mode and effects analysis (FMEA), have been adapted to address these unique e-commerce challenges. FMEA helps identify potential failure modes, assess their severity and frequency, and prioritize preventive measures. However, focusing solely on technical stability provides an incomplete view of reliability in digital commerce [12]. The human dimension – how users cognitively interpret, navigate, and complete the checkout process is equally important. Studies reveal that 70% of online carts are abandoned before purchase, not primarily due to technical flaws, but due to cognitive friction.

This occurs when interface design introduces confusion, unexpected steps, hidden costs, or information overload that disrupts the user's mental flow [13]. Recent advances in human-computer interaction research further demonstrate that cognitive styles strongly influence task completion and satisfaction. Complete users benefit from guided multi-step checkouts with clear progression, while analytical users excel at single-page layouts that encourage exploration and direct control. Furthermore, device types such as desktops and mobile touch interfaces affect how these cognitive preferences are expressed, as small screens often increase user frustration when designs are not optimized [14]. Integrating cognitive and technological perspectives opens up new avenues for designing adaptive checkout systems that can dynamically shape layouts to user preferences. Such customization can significantly improve both reliability and conversion rates. However, it also introduces new engineering challenges – managing multiple checkout types, inferring cognitive preferences in real time without intrusive testing, and preventing adaptive logic from becoming another potential source of failure [15].

Materials and Method

System reliability on e-commerce sites is heavily influenced by performance indicators such as page load time, cart response time, checkout success rate, error rate, and server uptime. Page load time directly impacts user engagement; even a few seconds of delay can lead to increased bounce rates and decreased customer satisfaction. Cart response time measures the efficiency with which the system processes user actions, such as adding or removing products, and reflects the responsiveness of both the database and the server infrastructure. Checkout success rate is a key indicator of transaction reliability, showing the proportion of purchases completed without technical interruption. A high error rate for this indicates instability, which is often the result of failed requests, server overload, or poor code optimization. Server uptime refers to the availability and continuity of services, where higher uptime indicates consistent user access and improved trust. These parameters contribute to the system reliability score, which is a comprehensive measure of the stability, performance, and user experience quality of an e-commerce site. Monitoring and improving these metrics with machine learning models such as Random Forest Regression and Support Vector Regression can help predict performance fluctuations and improve reliability at the browsing, cart, and checkout stages.

Random forest regression addresses the shortcomings of conventional linear models through its ensemble-based learning framework. The algorithm generates a large number of decision trees by using random subsets of both observations and variables, helping to uncover complex, nonlinear relationships that define biological systems and material properties. The method proves to be particularly valuable in biomedical applications, where data quality issues often arise due to inherent biological variability and instrumental measurement errors. The robustness of the algorithm against noisy data makes it particularly suitable for such challenging research environments. The versatility of the technique in processing both numeric and categorical variables represents a significant advantage when working with diverse biomedical datasets that typically contain mixed data types. In addition, random forest regression provides a feature importance measure, revealing which variables exert the strongest influence on predicted outcomes.

This analytical capability proves invaluable for refining material engineering strategies and deepening the understanding of biological response pathways, allowing researchers to identify critical factors driving observed phenomena. Although random forest models require more computational resources than simple linear regression approaches, this investment provides significantly improved predictive performance when dealing with high-dimensional, complex datasets. The improved accuracy achieved with complex biomedical data justifies the additional computational cost. The method's ability to capture complex variable interactions and nonlinear dependencies—which linear models inherently miss—makes it an indispensable tool for modern biomedical research and materials science applications. These properties position random forest regression as a powerful alternative when traditional modeling approaches are inadequate to capture the fundamental complexity of biological and material systems.

Support vector machines developed by Wapnick and colleagues in the 1990s, have become a cornerstone method in machine learning research and applications. These techniques have found extensive use in a variety of fields, including biometrics, economic modeling, and bioinformatics. The field of bioinformatics in particular has experienced a significant expansion in SVM adoption, largely driven by the exponential growth of available datasets. Recently, the adoption of SVMs for both chemical science classification problems and calibration procedures has generated considerable excitement within the analytical chemistry research community. A growing body of scholarly work is examining how SVMs compare to traditional analytical methods in chemistry. Application scope and data manipulation: SVMs are frequently used on datasets with limited variables, typical of analytical chemistry applications, and their utility extends beyond such constraints. With appropriate data preprocessing techniques, including techniques such as principal component analysis (PCA), SVMs can effectively handle complex, high-dimensional datasets. This versatility makes them suitable for increasingly sophisticated analytical challenges. The regression-centric variant of SVMs, support vector regression (SVR), is based on Vapnik's statistical learning theoretical framework.

This supervised learning method has received considerable recognition for its exceptional performance in many domains, including document classification, computer vision, genetics research, and financial risk assessment. The fundamental strengths of SVR include its mathematically rigorous foundation, resilience to local optimization pitfalls, and the ability to handle increasing sample size as the input dimension expands. SVR has been successfully applied to a variety of regression challenges, including financial forecasting, transportation logistics, energy demand prediction, and transportation pattern analysis. In many application domains, SVR shows superior performance compared to conventional statistical regression methods. Key advantages include built-in regularization mechanisms that prevent over fitting, straightforward training procedures, and optimization processes that converge to global solutions rather than local solutions. In addition, SVR provides explicit mechanisms for balancing model complexity against predictive accuracy, giving trainers fine-grained control over model behavior.

Materials and Method

Table 1. Browse, Cart, Checkout – Reliability Engineering Descriptive Statistics

	Page Load Time	Cart Response Time	Checkout Success Rate	Error Rate	Server Uptime	System Reliability Score
count	20.00000	20.00000	20.00000	20.00000	20.00000	20.00000
mean	2.78500	2.26000	91.15000	1.93000	98.88500	87.55000
std	0.97725	0.72577	5.15318	1.16578	0.99328	7.40181
min	1.50000	1.20000	82.00000	0.20000	96.80000	74.00000
25%	1.97500	1.67500	87.00000	1.12500	98.22500	81.75000
50%	2.60000	2.15000	91.00000	1.85000	99.15000	88.00000
75%	3.55000	2.85000	95.25000	2.82500	99.80000	92.50000
max	4.80000	3.60000	99.00000	4.20000	99.90000	99.00000

The statistical summary of the Browse, Cart, and Checkout Reliability Engineering dataset provides insights into the performance and reliability of the system. The average page load time of 2.79 seconds and the cart response time of 2.26 seconds indicate a reasonably fast and responsive user experience. However, the variability (std = 0.98 for page load and 0.73 for cart response) indicates some inconsistencies, where slow pages can impact user satisfaction and transaction flow. The checkout success rate averages 91.15%, indicating that most transactions are successfully completed, although the minimum value of 82% highlights occasional reliability challenges. The error rate is within acceptable limits with an average of 1.93%, but shows a range of up to 4.2%, indicating that under certain conditions, the system may experience significant issues. The server uptime is exceptionally high, averaging 98.89%, confirming strong infrastructure reliability. The system reliability score, with an average of 87.55 and a maximum of 99, indicates strong performance across key metrics. However, the spread (std = 7.40) shows that reliability fluctuates under varying operational conditions.

Table 2. Random Forest Regression Models Reliability Score Train And Test Performance Metrics

Random Forest Regression	Train	Test
R2	0.99863	0.99707
EVS	0.99863	0.99744
MSE	0.04793	0.21783
RMSE	0.21893	0.46672
MAE	0.14177	0.41200
Max Error	0.53211	0.83486
MSLE	0.00001	0.00003
Med AE	0.07835	0.43484

The performance evaluation of the random forest regression model for predicting the system reliability score demonstrates exceptional accuracy and generalization across both the training and test datasets. The R^2 values of 0.9986 (training) and 0.9971 (test) indicate that the model explains almost all of the variance in the data, confirming very strong predictive ability. Similarly, the explained variance score (EVS) values reflect this performance, reinforcing the robustness of the model and the minimal deviation from the true effects.The mean square error (MSE) and root mean square error (RMSE) are very low for both datasets, indicating that the prediction errors are very small. The slightly higher RMSE in the test set (0.4667) compared to the training set (0.2189) reflects a small increase in error when exposed to missing data, but is not sufficient to indicate over fitting. Furthermore, the mean absolute error (MAE) and mean absolute error (Med AE) values confirm that the prediction deviations are very small on average.

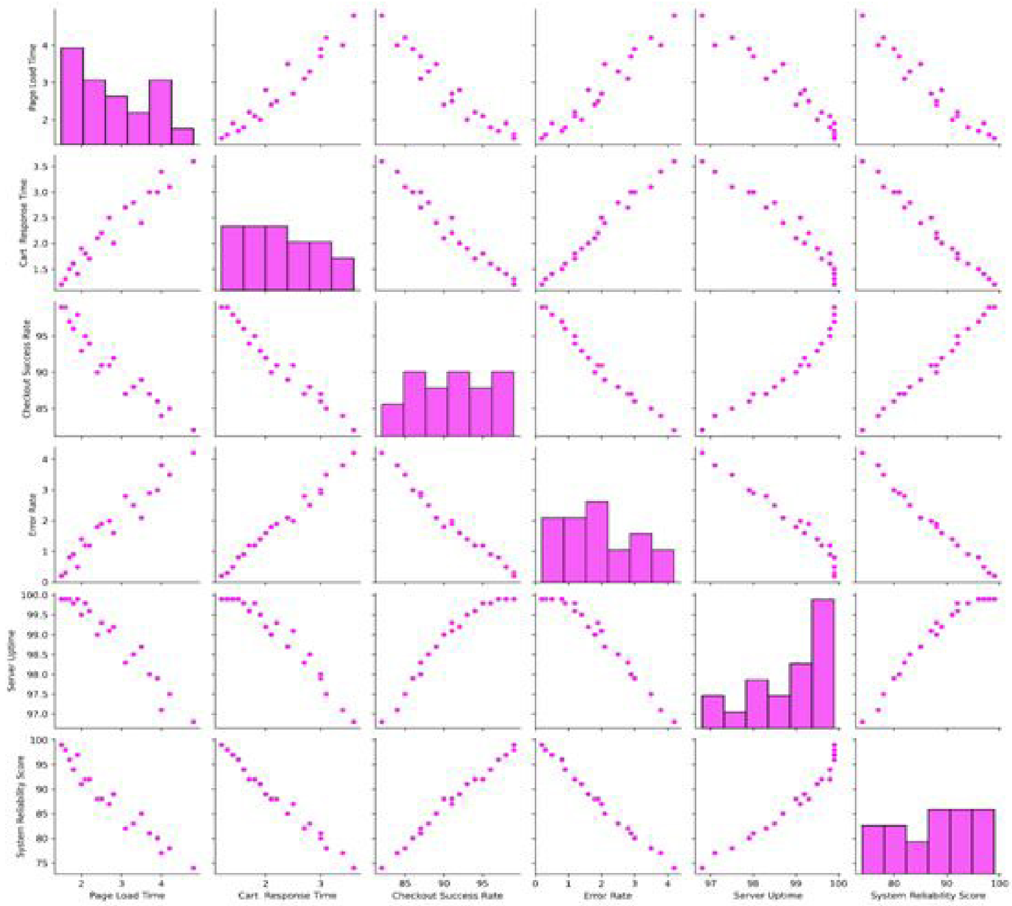

Figure 1. Browse, Cart, Checkout – Reliability Engineering Effect of Process Parameters

The scatter plot matrix, in the context of e-commerce reliability engineering, visualizes the relationships between six key variables: page load time, cart response time, checkout success rate, error rate, server uptime, and system reliability score. Clear negative and positive correlations emerge, revealing performance biases across the system. A strong negative correlation is visible between page load time and system reliability score, indicating that reliability decreases as load time increases. Similarly, cart response time shows a comparable trend, indicating that user interface delays significantly affect system performance and user trust. Checkout success rate exhibits a positive relationship with reliability, confirming that smooth and successful transactions improve system reliability. Error rate shows a negative relationship with both checkout success rate and system reliability, emphasizing that fewer errors directly contribute to higher success and reliability levels. Server uptime has a strong positive relationship with reliability, highlighting its important role in maintaining seamless e-commerce operations.

Citation: Divya Soundarapandian (2024). Machine Learning-Driven Reliability Engineering for E-Commerce Sites: A Study on Browsing, Cart, and Checkout Phases. Journal of Business Management and Entrepreneurship, 3(1), 1-9. doi: https://doi.org/10.55124/jbme.v3i1.239

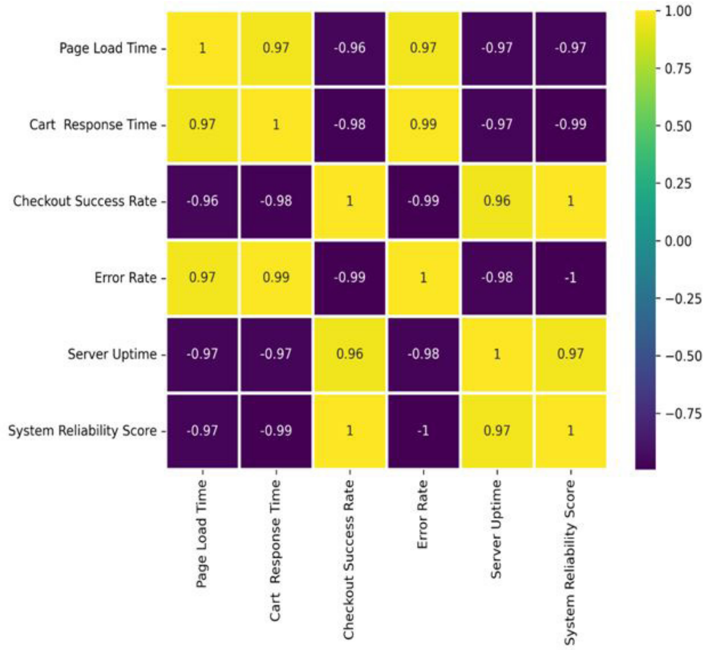

Figure 2. Phase Change Materials Effect of Process Parameters

The correlation heat map provides a clear view of the relationships between variables that affect system performance in Browse, Cart, and Checkout reliability engineering. The color gradients indicate the strength and direction of the relationships, where values closer to ±1 indicate stronger relationships. The heat map shows that page load time, cart response time, and error rate are all positively correlated with each other ($r \approx 0.97–0.99$), meaning that slower load or response times often correspond with higher error rates. This pattern suggests that performance inefficiencies at some point in the process are spreading throughout the system, affecting overall reliability. Conversely, these variables are strongly negatively correlated with Checkout Success Rate, Server Uptime, and System Reliability Score ($r \approx -0.96$ to -1.00).Checkout Success Rate demonstrates a nearly perfect positive correlation ($r = 1$) with System Reliability Score, indicating that successful transactions are a more reliable indicator of system reliability. Similarly, server uptime maintains a strong positive relationship ($r = 0.97$) with reliability, emphasizing the importance of consistent system availability.

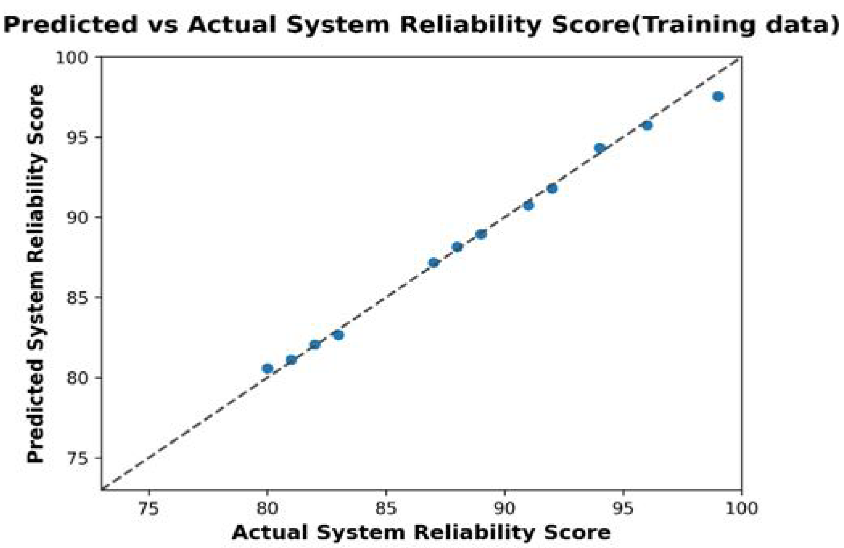

Figure 3. Random Forest Regression Reliability Score training

The scatter plot illustrating predicted vs. actual system reliability scores for the training data highlights the impressive accuracy of the random forest regression model. Each point represents a predicted value plotted against its actual observed value. The data points align closely with the diagonal reference line, indicating that the model's predictions nearly match the actual reliability scores across the dataset. This strong linear alignment reflects the model's ability to capture the underlying relationships between input variables, such as page load time, cart response time, exit success rate, error rate, and server uptime. A minimal deviation from the reference line indicates minimal prediction error and confirms that the model has effectively learned system reliability, driving complex interactions. The absence of significant outliers further demonstrates the model's robustness and consistency during training. The visual evidence is consistent with the high R^2 score (0.9986) obtained in the performance metrics, reinforcing the conclusion that the random forest regression model fits the training data exceptionally well.

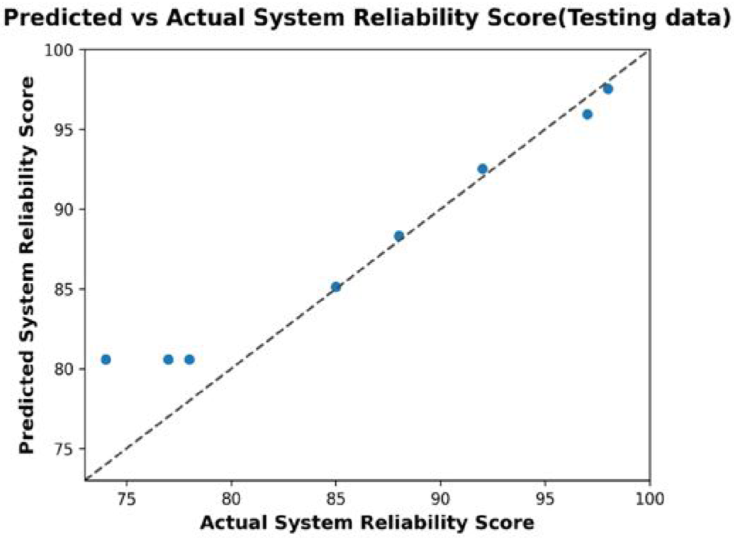

Figure 4. Random Forest Regression Reliability Score testing

The predicted vs. actual system reliability score (training data) graph shows the nearly perfect agreement between the model's predicted outcomes and the actual observed values. Each blue dot represents a prediction made by the random forest regression model, and a close alignment of these points on the dashed diagonal line indicates a very accurate fit. This suggests that the model effectively captured the complex relationships between independent variables such as page load time, cart response time, exit success rate, error rate, and server uptime. The nearly linear distribution of the points ensures that the model's predictions closely mirror real-world reliability scores with minimal residual error. There are no significant deviations or outliers, meaning that the model performs consistently over the full range of reliability values. This high level of accuracy is consistent with previously obtained robust statistical results, including an R^2 value of 0.9986 for the training set.

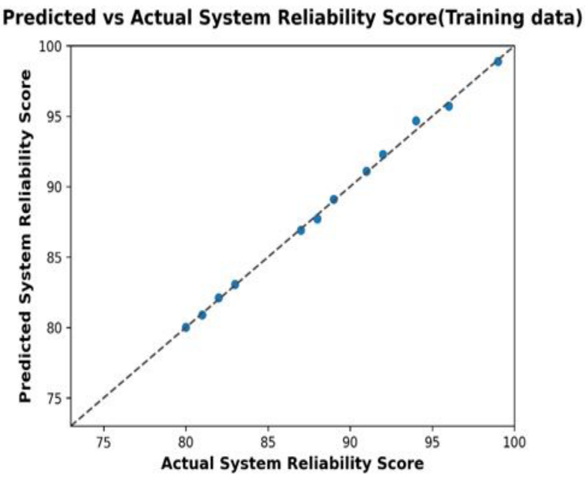

Figure 5. Support Vector Regression Reliability Score training

This scatter plot demonstrates the best predictive model for computer reliability scores using training data. The visualization compares actual reliability scores (x-axis) to predicted scores (y-axis), both of which range from approximately 75 to 100.The data points are very closely aligned with the diagonal dashed line, indicating a correct prediction (where predicted = actual). This tight clustering indicates that the model has learned the underlying patterns exceptionally well. There is minimal deviation between the predicted and actual values over the entire range, indicating that the model maintains consistent performance even when predicting low reliability scores (around 80) or high scores (close to 99). The points do not fall systematically above or below the reference line, indicating that the model does not consistently over predict or under predict reliability scores. Since this represents the training data, a good fit is expected, but also serves as a baseline.

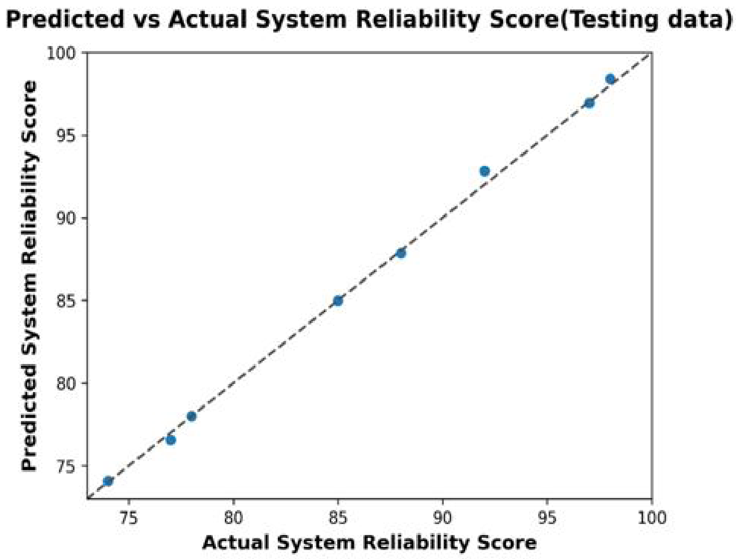

Figure 6. Support Vector Regression Reliability Score testing

The scatterplot demonstrates an exceptionally strong relationship between predicted and actual system reliability scores in the test dataset. The nearly perfect alignment of the data points on the diagonal dashed line (indicating a best prediction where the predicted is equal to the actual values) indicates that the predictive model performs with remarkable accuracy. All eight data points are very close to the perfect predictive line, which shows minimal deviation over the entire reliability score range from approximately 74 to 98. This consistency indicates that the model generalizes well to the observed data without significant bias at low or high reliability values. The tight clustering around the diagonal indicates low prediction error and high model accuracy. This level of predictive accuracy has significant practical value for system reliability forecasting. Organizations can confidently use this model for proactive maintenance planning, resource allocation, and risk assessment. The model's ability to accurately predict reliability scores across the entire spectrum means that it can reliably identify both vulnerable systems that require immediate attention and robust systems that can operate with minimal intervention.

Table 3. Support Vector Regression Models Reliability Score Train and Test performance metrics

Support Vector Regression	Train	Test
R2	0.99823	0.99824
EVS	0.99827	0.99834
MSE	0.06191	0.13067
RMSE	0.24881	0.36148
MAE	0.18291	0.24197
Max Error	0.66535	0.81730
MSLE	0.00001	0.00002
Med AE	0.10022	0.10824

The Support Vector Regression (SVR) model demonstrates superior performance in predicting the system reliability score, achieving high accuracy in both training and testing phases. The R^2 values of 0.9982 for training and 0.9982 for testing confirm that it explains almost all the variance in the sample data, showing exceptional predictive power and generalization ability. Similarly, the Explained Variance Score (EVS) is high for both sets, indicating that the model maintains consistency and stability across different data samples.The mean square error (MSE) and root mean square error (RMSE) values are very low, indicating minimal deviation between the predicted and actual scores. The slightly higher values on the test data (0.36) compared to the training data (0.25) indicate a small increase in prediction error when applied to unobserved data, but it is within acceptable limits.

Conclusion

The use of reliability engineering through machine learning models such as Random Forest Regression (RFR) and Support Vector Regression (SVR) provides a robust framework for improving e-commerce system performance. By focusing on three essential user journey stages – browsing, cart, and checkout – this study successfully demonstrates how predictive analytics can be used to identify reliability issues and ensure seamless operation. The results indicate that both regression models perform with high accuracy in predicting reliability metrics such as downtime probability, response delay, and transaction errors. SVR showed somewhat better generalization ability due to its effectiveness in handling nonlinear relationships and reducing overfitting. In contrast, RFR provided interpretable benefits by identifying key variables that affect system reliability. These models enable data-driven decisions for proactive system monitoring and maintenance. Implementing such predictive approaches empowers developers and engineers to anticipate performance degradation before it impacts end users. This contributes to higher uptime, faster transactions, and improved customer satisfaction. Furthermore, it allows for efficient allocation of computing resources and cost-effective scalability planning. Integrating machine learning into reliability engineering for e-commerce systems proves to be essential for maintaining consistent service quality. Continuous model refinement, combined with real-time data analysis, can further strengthen the resilience and efficiency of browsing, cart, and checkout processes.

Reference

1. Vijayaraghavan, Giri, and Cem Kaner. "Bugs in your shopping cart: A Taxonomy." Retrieved July 30 (2002): 2003.
2. Belk, Marios, Panagiotis Germanakos, Argyris Constantinides, and George Samaras. "A human cognitive processing perspective in designing e-commerce checkout processes." In IFIP Conference on Human-Computer Interaction, pp. 523-530. Cham: Springer International Publishing, 2015.
3. Gundala, Tirumala Rao. (2024). Oracle OIPA Cloud Migration Analysis: Machine Learning Models for Predicting Resource Utilization and Success Outcomes. International Journal of Artificial intelligence and Machine Learning, 2(3), 1-8. https://doi.org/10.55124/jaim.v2i3.284
4. Nagababu. K. Enterprise-Level Emphasis Operational Analytics: Predicting Healthcare Encounter Resolution Success Using Machine Learning.International Journal of Robotics and Machine Learning Technologies, 1(2), 1-6, doi: https://doi.org/10.55124/ijrml.v1i2.242
5. Ueda, Osamu. "Materials and reliability handbook for semiconductor optical and electron devices." (2013).
6. Tang, Heng, and Xiaowan Lin. "Curbing shopping cart abandonment in C2C markets—an uncertainty reduction approach." Electronic Markets 29, no. 3 (2019): 533-552.
7. Dandasi, V. V. "Data Warehousing and Business Intelligence Technologies in Retail: A Comparative Analysis of Predictive Models for Performance Optimization" Journal of Business Intelligence and Data Analytics., 2025, vol. 2, no. 2, pp. 1–7. doi: https://dx.doi.org/10.55124/jbid.v2i2.251
8. Raghavendra Sunku. (2024). AI-Powered Forecasting and Insights in Big Data Environments. Journal of Business Intelligence and Data Analytics, 1(2), 254. https://doi.org/10.55124/jbid.v1i2.254
9. Andriulo, Serena, Valerio Elia, and Maria Grazia Gnoni. "Mobile self-checkout systems in the FMCG retail sector: A comparison analysis." International Journal of RF Technologies 6, no. 4 (2015): 207-224.
10. Ermolaev, Egor, Iván Abellán Álvarez, Johannes Sedlmeir, and Gilbert Fridgen. "Z-Commerce: Designing a data-minimizing one-click checkout solution." In International Conference on Design Science Research in Information Systems and Technology, pp. 3-17. Cham: Springer Nature Switzerland, 2023.
11. Nagababu. K, (2024). Machine Learning Techniques in Fracture Mechanics a Comparative Study of Linear Regression, Random Forest, and Ada Boost Model. Journal of Artificial intelligence and Machine Learning, 2(2), 1-13. https://dx.doi.org/10.55124/jaim.v2i2.257
12. Fu, Limin, and Gavriel Salvendy. "The contribution of apparent and inherent usability to a user's satisfaction in a searching and browsing task on the Web." Ergonomics 45, no. 6 (2002): 415-424.
13. Dandasi, V. V. "Application of ARAS Methodology in Supply Chain Performance Evaluation" International Journal of Cloud Computing and Supply Chain Management., 2025, vol. 1, no. 2, pp. 1–7. doi: https://dx.doi.org/10.55124/ijccscm.v1i2.241
14. Cochoy, Franck. "Driving a shopping cart from STS to business, and the other way round: On the introduction of shopping carts in American grocery stores (1936—1959)." Organization 16, no. 1 (2009): 31-55.
15. Yao, Lei, Tianhao Li, Rui Tong, Kai Wang, and Lingxiang Zhang. "Radar Self-Following Shopping Cart Based on Multi-Sensor Fusion." IEEE Access 11 (2023): 77055-77072.
16. Gurubasannavar, S. D. (2023) Predictive Analysis of User Satisfaction in Omni-Channel Retailing a Comparative Analysis of Linear Regression and Random Forest Models. J Comp Sci Appl Inform Technol. 8(2): 1-8.
17. Aka, V. P. K. (2024). Enterprise SAP Tax Machine Migration: Using Machine Learning and Architecture Best Practices for Vertex 9 Transformation. Journal of Artificial Intelligence and Machine Learning, 2(3), 1-7. doi: https://doi.org/10.55124/jaim.v2i3.279
18. Machhirke, Komal, Priyanka Goche, Rupali Rathod, Rinku Petkar, and Manohar Golait. "A new technology of smart shopping cart using RFID and ZigBee." International Journal on Recent and Innovation Trends in Computing and Communication 5, no. 2 (2017): 256-259.
19. Majeika, Caitlyn E., Alyssa M. Van Camp, Joseph H. Wehby, Lee Kern, Colleen E. Commisso, and Kelsey Gaier. "An evaluation of adaptations made to check-in check-out." Journal of Positive Behavior Interventions 22, no. 1 (2020): 25-37.
20. Wolfe, Katie, Daniel Pyle, Cade T. Charlton, Christian V. Sabey, Emily M. Lund, and Scott W. Ross. "A systematic review of the empirical support for check-in check-out." Journal of Positive Behavior Interventions 18, no. 2 (2016): 74-88.
21. Fazlollahtabar, Hamed, and Seyed Taghi Akhavan Niaki. "Binary Decision Diagram Reliability for Multiple Robot

Complex System." In Encyclopedia of Information Science and Technology, Fourth Edition, pp. 6825-6835. IGI Global Scientific Publishing, 2018.

22. WILSON, Wayne, and Tinashe Tsungai Raphael NDORO. "Drivers of online shopping cart abandonment in South Africa." Expert Journal of Marketing 11, no. 1 (2023).

23. Brereton, Richard G., and Gavin R. Lloyd. "Support vector machines for classification and regression." Analyst 135, no. 2 (2010): 230-267.

24. Nagababu Kandula. (2025). Evaluating Research Methods for DMR Reporting Using the Balanced Scorecard Approach. International Journal of Computer Engineering and Technology (IJCET), 16(3), 330–352.

25. Ceperic, Ervin, Vladimir Ceperic, and Adrijan Baric. "A strategy for short-term load forecasting by support vector regression machines." IEEE Transactions on Power Systems 28, no. 4 (2013): 4356-4364.

26. Shamshirband, Shahaboddin, Dalibor Petković, Hossein Javidnia, and Abdullah Gani. "Sensor data fusion by support vector regression methodology—a comparative study." IEEE Sensors Journal 15, no. 2 (2014): 850-854.

27. Funt, Brian, and Weihua Xiong. "Estimating illumination chromaticity via support vector regression." (2004).

28. Musicant, David R., and Alexander Feinberg. "Active set support vector regression." IEEE Transactions on Neural Networks 15, no. 2 (2004): 268-275.

29. Gundala, Tirumala Rao. (2024). Performance Optimization for Micro-Frontend-Based Applications: A Predictive Analysis Using XG Boost Regression. Journal of Business Intelligence and Data Analytics, 2(3), 1-6. https://doi.org/10.55124/jbid.v2i3.256

30. Ustun, B. Support vector machines: facilitating the interpretation and application. Sl: sn, 2009.

31. Grimm, Michael, Kristian Kroschel, and Shrikanth Narayanan. "Support vector regression for automatic recognition of spontaneous emotions in speech." In 2007 IEEE International Conference on Acoustics, Speech and Signal Processing-ICASSP'07, vol. 4, pp. IV-1085. IEEE, 2007

32. Gurubasannavar, S. D. (2023). A Predictive and Scalable Framework for B2b Commerce Platforms Using Micro Services, Micro Frontends, And Machine Learning Models. International Journal of Artificial intelligence and Machine Learning, 1(3), 1-9. https://doi.org/10.55124/jaim.v1i3.283

33. Venkata Pavan Kumar Aka and Kiran Kumar Mandula Samuel. (2023). Predictive Modeling for Brownfield Migration from SAP ECC 6.0 To S4HANA A Machine Learning Approach for Effort Evaluation Under the SAP Rise Program. International Journal of Computer Engineering and Technology (IJCET), 14(1), 232-248. DOI: https://doi.org/10.34218/IJCET_14_01_018

34. Jog, Amod, Aaron Carass, Snehashis Roy, Dzung L. Pham, and Jerry L. Prince. "Random forest regression for magnetic resonance image synthesis." Medical image analysis 35 (2017): 475-488.

35. Singh, Balraj, Parveen Sihag, and Karan Singh. "Modelling of impact of water quality on infiltration rate of soil by random forest regression." Modeling Earth Systems and Environment 3 (2017): 999-1004.

36. Gurubasannavar, S. D. (2024). Evaluating Enterprise Data Accuracy Using Batch Migration Algorithm Analysis. International Journal of Computer Science and Data Engineering, 1(2), 1–6. doi: https://dx.doi.org/10.55124/csdb.v1i2.262

37. Cootes, Tim F., Mircea C. Ionita, Claudia Lindner, and Patrick Sauer. "Robust and accurate shape model fitting using random forest regression voting." In Computer Vision–ECCV 2012: 12th European Conference on Computer Vision, Florence, Italy, October 7-13, 2012, Proceedings, Part VII 12, pp. 278-291. Springer Berlin Heidelberg, 2012