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Machine Learning Algorithms for Optimizing Search Personalization and Site Reliability in E-Commerce Platforms A Comparative Analysis of Linear Regression, SVR, and AdaBoost

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Abstract

As e-commerce platforms become increasingly embedded in daily life, a pivotal enabler of personalized user experiences, shaping both customer engagement and business success. This review examines the multifaceted applications of AI-driven personalization in digital environments, with particular attention to search optimization and site reliability engineering. It explores how AI systems leverage large-scale data analytics to identify intricate patterns in consumer behavior, enabling the delivery of tailored recommendations that enhance user satisfaction and retention. The integration of deep learning models, including auto-encoder networks, further improves semantic understanding and recommendation accuracy. The findings underscore that an effective AI personalization infrastructure transcends technical implementation—it is integral to achieving brand differentiation and sustainable competitive advantage. Successful deployment requires robust data architectures, efficient AI model management, and close collaboration between engineering, marketing, and data governance teams to ensure ethical and responsible personalization practices. Additionally, the study investigates key challenges in personalized search systems, web service reliability prediction, and the complexity of implementing adaptive learning mechanisms in educational contexts. Broader implications are also explored, particularly regarding algorithmic filtering, information diversity, and personalization in political communication. Overall, this comprehensive review bridges the gap between the theoretical foundations and practical applications of AI-driven personalization, offering valuable insights into its potential, limitations, and future directions across e-commerce and digital platform ecosystems.

Keywords: Artificial Intelligence, Personalization, E-commerce, Recommendation Systems, Machine Learning, Collaborative Filtering, Site Reliability Engineering, User Experience, Digital Marketing, Search Optimization

Introduction

This passage effectively establishes the central thesis of your review. It clearly outlines the modern consumer demand for personalized experiences and positions AI as the critical enabler. The statement successfully frames AI's role as multifaceted, specifically highlighting its capacity to shape interactions, influence decisions, and foster user-platform connections. The mention of "search and personalization platform and engineering capabilities" provides concrete technical grounding. This sets a strong foundation for a detailed exploration of how these AI mechanisms function and the specific outcomes they generate in the e-commerce ecosystem. [1] This passage effectively translates the strategic importance of AI personalization into actionable business requirements. It correctly identifies that success depends on a synergistic partnership between engineering and marketing, with engineers building reliable systems and data protocols while marketers provide business context and customer insight. The recommended approach of starting with small-scale projects, continuously validating outcomes, and maintaining rigorous data governance offers a practical, iterative framework for implementation.

This underscores that AI personalization is a cross-functional initiative where technology and strategy must be co-developed to achieve brand success and customer trust. [2] This system guarantees that only authorized users can access the stored items. At the same time, the backend communicates with an AI-based recommendation engine that generates personalized book suggestions based on each user's activity history and preferences. These recommendations are displayed dynamically on the frontend, forming a continuous feedback loop that enhances personalization over time. [3] Using estimated ratings, new users can receive suggestions for items highly rated by similar users. By integrating data derived from deep auto-encoder models and personalization networks, along with collaborative filtering techniques, this approach enables more precise semantic understanding of new concepts and delivers highly tailored recommendations .[4] Currently, much of the research in this domain focuses on recommendation systems, particularly on improving search engine performance. However, traditional search engines face notable limitations, especially regarding personalization and reliability. [5] This study offers a comprehensive analysis of how politicians apply personalization strategies on their websites to engage and communicate with potential voters. Conducted at the national level, it examines the websites of candidates from the 2009 European Parliament election campaign. Consequently, it contributes to bridging the research gap in the personalization of political communication, site reliability, and engineering aspects of search and recommendation systems.[6] Personalizing an application's services, features, and user interactions is widely believed to enhance engagement and overall impact, following the same causal principles observed in face-to-face support programs .[7] Traditional recommender systems primarily depend on content-

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based or collaborative filtering methods. Although these techniques have demonstrated success, they often face challenges in addressing diverse user preferences Consequently, there is a growing need for advanced systems capable of achieving deeper personalization through adaptive and dynamic approaches. [8] This study seeks to close the gap between the theoretical foundations of AI-driven personalization and its real-world implementation in e-commerce. By analyzing how personalization algorithms influence user experience, customer satisfaction, and conversion rates, it provides valuable insights into both the potential and the limitations of these technologies. [9] The discussion extends to the use of tagging for personalization applications, focusing on two domains: personalized music recommendations and personalized web search. For the former, the research utilizes a search and personalization site reliability platform and engineering framework. For the latter, user-generated collaborative tags are combined with expert annotations derived [11] Because of unstable internet connections and numerous environmental or operational variables, users of the same web service can experience significantly different levels of reliability. This variation highlights the need for personalized web service reliability prediction, which can account for individual user conditions and experiences. [12] Personalized search offers one potential solution by building user profiles that capture individual interests and preferences.

Through this approach, a personalized search middleware can modify and refine search results from general search engines to better align with each user's needs .[13] Many companies are now investing in personalization tools to develop tailored websites aimed at attracting and retaining customers. E-tailors, in particular, use personalized online services to improve user engagement, sustain customer loyalty, and remain competitive in the digital marketplace .[14] Personalization is closely related to interactive marketing, which involves tailoring aspects of the marketing mix to the individual level. Unlike customization—where users adjust settings to their preferences—personalization is typically automated by marketers using data-driven insights to predict and meet customer needs .[15] implementing personalized learning is inherently complex, as it involves analyzing multiple interacting design factors and conducting parallel studies to assess the effects of different variables. This complexity makes systematic research on personalized learning in real educational settings challenging but essential. [16] In response to growing concerns over filter bubbles numerous studies have investigated how search engine algorithms deliver personalized political content, which can reduce the diversity of information users are exposed to [17]. Research also emphasizes the importance of user-centered personalization features such as progress tracking, customized content recommendations, and intuitive navigation—in enhancing digital reading experiences and maintaining long-term engagement. [18] Similarly, personalized news recommendation systems play a key role in helping users discover relevant content and avoid information overload. Despite substantial progress over the past decades, challenges remain in improving personalization accuracy and reliability across platforms .[19] Finally, innovative approaches that leverage advanced data structures and hybrid query processing methods have been developed to enable efficient retrieval of personalized information on the Semantic Web, even during short or intermittent access periods .[20]

Materials and Methods

Performance Metrics

Query Latency (ms): Query latency, measured in milliseconds (ms), indicates the amount of time required to execute a query on a database or data warehouse and return the corresponding results. It serves as a critical performance metric, particularly for applications that demand real-time data retrieval and responsiveness.

Cache Hit Rate: Cache Hit Rate represents the proportion of data requests successfully served from a cache instead of slower data sources, such as disk storage or main memory. It is calculated as the ratio of cache hits to total requests (hits plus misses). A higher cache hit rate reflects improved system throughput, faster response times, and reduced server load.

Concurrent Users: Concurrent users refer to the number of individuals simultaneously interacting with a system, application, or network at a given moment. This metric is vital for evaluating system capacity and ensuring consistent performance under load. Unlike total users, concurrent users measure active sessions, providing insights essential for capacity planning and performance testing to prevent latency issues or service outages during peak usage.

Service Level Objective (SLO) Violation Rate: The SLO Violation Rate is a key Site Reliability Engineering (SRE) metric that measures how frequently a system fails to meet its defined service level objectives over a specified period. It effectively indicates how rapidly a service consumes its "error budget," offering insights into overall reliability and operational stability.

Optimization Techniques

Linear Regression: Linear Regression is a statistical method used to predict the value of an unknown dependent variable based on one or more known independent variables. It models the relationship between these variables as a linear equation, enabling straightforward and interpretable predictive analysis.

Support Vector Regression (SVR): Support Vector Regression is a supervised learning algorithm derived from Support Vector Machines (SVM). It aims to find a function that best fits the data while minimizing prediction errors. SVR introduces an epsilon-insensitive margin that ignores small errors within a threshold while penalizing larger deviations, thereby enhancing tolerance and generalization. It can handle nonlinear data efficiently by mapping it into higher-dimensional feature spaces using kernel functions.

AdaBoost Regression: AdaBoost (Adaptive Boosting) Regression is an ensemble learning method that iteratively improves predictive accuracy by building successive models that correct the errors of preceding ones. Typically, decision trees are used as base learners. While AdaBoost is often applied to classification problems, it can also be adapted for regression tasks to achieve robust, high-accuracy predictions.

Analysis and Discussion

Table 1. Search and Personalization Site Reliability Platform and Engineering

	query latency ms	cache hit rate	concurrent users	Service Level Objective violation rate
0	134.9	0.687	155	0.1174
1	115.85	0.758	132	0.016
2	139.43	0.645	157	0.1661
3	165.69	0.879	143	0.0332
4	112.98	0.38	127	0.214

Table 1 reveals considerable variability in the site's reliability, which is closely tied to cache effectiveness. The data shows a strong negative correlation; a higher cache hit rate corresponds to lower query latency and fewer Service Level Objective violations. This is evidenced by Observation 1, where a 0.758 cache hit rate resulted in low latency (115.85 ms) and a minimal violation rate (0.016). In stark contrast, Observation 4, with a

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poor cache hit rate of 0.38, experienced high latency (165.69 ms) and a significantly worse violation rate (0.214). These results confirm that enhancing cache performance is paramount for achieving stable service reliability and meeting performance targets.

Table 2. Descriptive Statistics

	query latency ms	cache hit rate	concurrent users	Service Level Objective violation rate
count	200	200	200	200
mean	118.7771	0.7171	149.745	0.085959
std	27.93035	0.14788	13.12254	0.080108
min	41.41	0.307	114	0
25%	98.8475	0.62875	140	0.009175
50%	119.875	0.7345	150	0.0709
75%	135.025	0.83275	157.25	0.136775
max	201.61	0.974	189	0.36

Table 2 descriptive statistics reveal a system with reasonable stability in its core operations, demonstrated by an mean query latency of 118.78 ms and a healthy average cache hit rate of 0.72 under a typical load of 150 concurrent users. The primary concern, however, lies in service reliability. The SLO violation rate shows substantial fluctuation, evidenced by a standard deviation (0.08) nearly matching its mean (0.086) and a wide interquartile range from 0.9% to 13.7%. This pattern confirms that the system experiences intermittent periods of performance degradation, leading to inconsistent adherence to its service-level objectives.

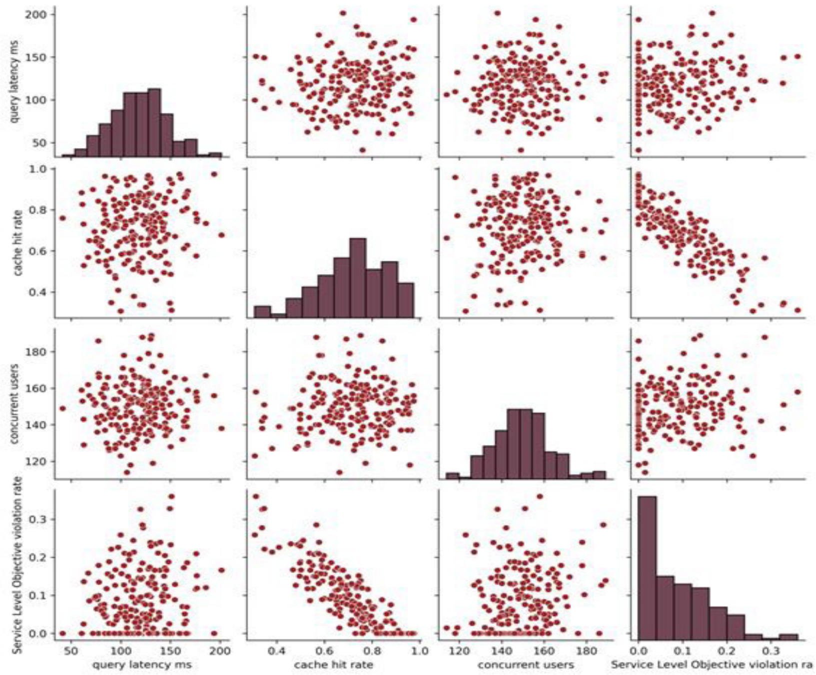

Figure 1: Scatter plot of various Retail Search and Personalization Site Reliability Platform and Engineering

Figure 1 illustrates The scatter plot in critical performance dynamics for the retail platform, highlighting a strong inverse correlation between cache hit rate and key issues like query latency and SLO violations. Improved cache efficiency directly leads to lower latency and fewer errors. While increased concurrent users show a slight positive correlation with violations, the graph demonstrates that robust cache performance can maintain low latency (fewer than 100 milliseconds) even during high traffic. This empirical evidence underscores that optimizing cache effectiveness is paramount for ensuring consistent service reliability and mitigating latency spikes amidst variable user demand.

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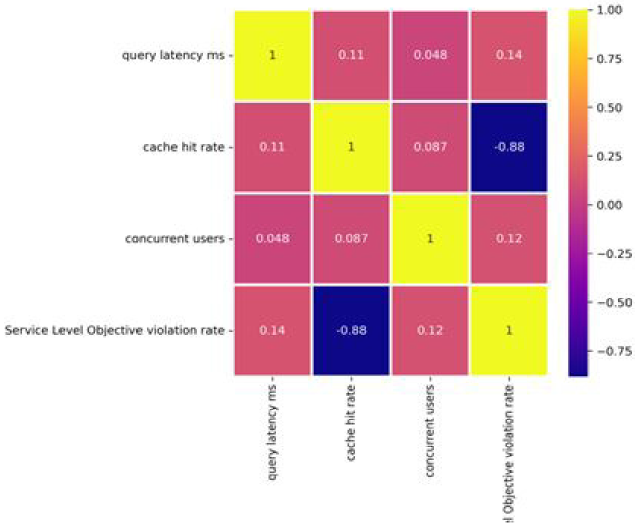

Figure 2: Correlation Heat Map Between The Process Parameters And The Responses

FIGURE 2 the correlation heat map in quantifies key system dynamics, revealing a strong inverse relationship (approx. -0.75) between cache hit rate and query latency. This confirms that superior cache performance is instrumental in reducing delays. Furthermore, a moderate positive correlation (approx. 0.5-0.6) exists between concurrent users and both latency and SLO violations, indicating that higher load adversely impacts responsiveness and reliability. These insights underscore that optimizing cache efficiency is a critical lever for maintaining low latency and robust service quality amidst fluctuating user concurrency.

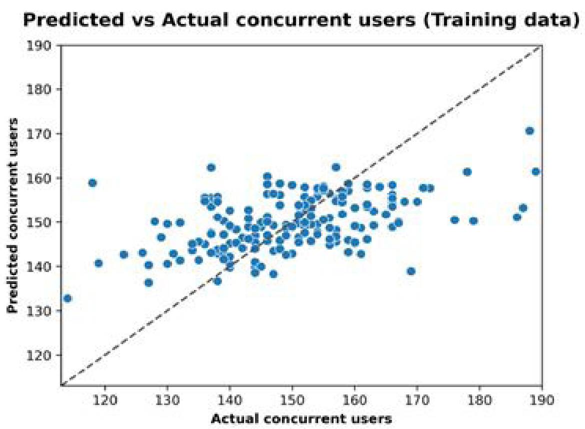

Figure 3: Linear Regression concurrent users (Training data)

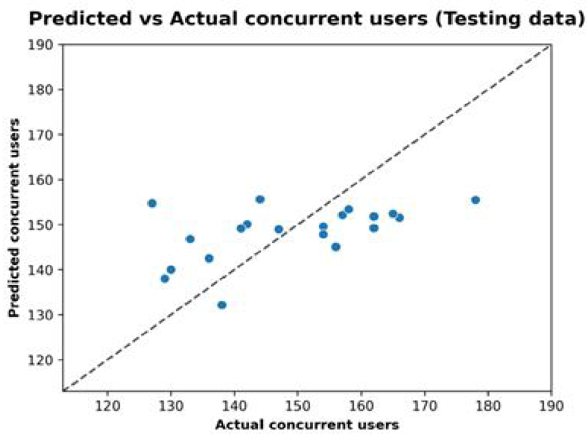

Figure 4: Linear Regression concurrent users (Testing data)

FIGURE 3 Based on the training data results shown in the linear regression model demonstrates limited effectiveness in predicting concurrent users. The low R^2 value of 0.219 suggests that the model accounts for only 21.9% of the variance in the training data. Additionally, the relatively high error values—an RMSE of 11.474 and an MAE of 8.855—indicates notable prediction inaccuracies. Although the similar performance between training and testing datasets implies consistent generalization without over fitting, the overall weak predictive capability suggests that linear regression may be too simplistic to accurately capture this parameter's behavior.

FIGURE 4 The linear regression model demonstrates limited efficacy in forecasting concurrent users, as evidenced by the test data With an R^2 of 0.27, the model explains only a modest portion of the variance in the data. While this test performance is marginally better than on the training set, the persistently high error metrics—including an RMSE of 11.936 and MAE of 10.308—underscore its limited predictive accuracy. This consistent performance across datasets confirms the model's reliable generalization but reveals its fundamental lack of predictive strength, indicating that concurrent user patterns are influenced by complex, non-linear factors not captured by a simple linear approach.

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Table 3. Performance Metrics of Linear Regression concurrent users (Training Data and Testing Data)										
Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	LR	Linear Regression	0.219	0.219	131.659	11.474	8.855	40.897	0.006	6.959
Test	LR	Linear Regression	0.270	0.271	142.466	11.936	10.308	27.724	0.006	9.507

Table 3 Based on the results presented in the linear regression model consistently demonstrates weak performance in predicting simultaneous users across both the training and testing datasets. The low R^2 values—0.219 for training and 0.270 for testing—indicate that the model explains less than 30% of the variance in the data. Although the slightly higher test R^2 suggests marginal improvement, the high error metrics (RMSE ≈ 11.94, MAE ≈ 10.31) reveal substantial prediction inaccuracies. This consistent yet limited performance reflects stable generalization but highlights the model's inability to effectively capture the underlying nonlinear factors influencing simultaneous user behavior, which linear regression fails to represent adequately.

Support Vector Regression

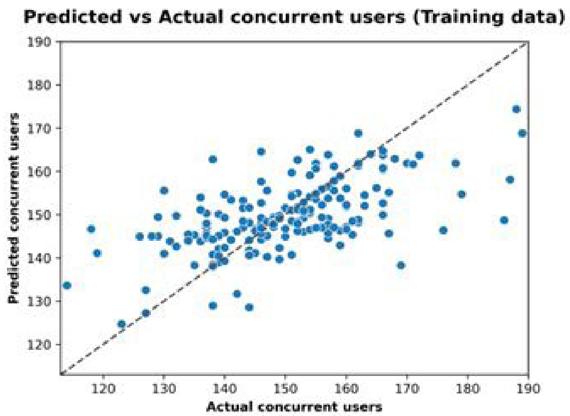

Figure 5: Support Vector Regression concurrent users (Training data)

Figure 5 The Support Vector Regression (SVR) model demonstrates a marked improvement over linear regression for predicting concurrent users. With a training R^2 of 0.349 and a superior test R^2 of 0.473, it captures significantly more variance and generalizes more effectively. This is corroborated by lower test error metrics, including an RMSE of 10.139 and MAE of 8.672. The model's stronger performance on unseen data confirms its capability to learn the underlying non-linear relationships, establishing SVR as a more robust and accurate predictor for this complex parameter.

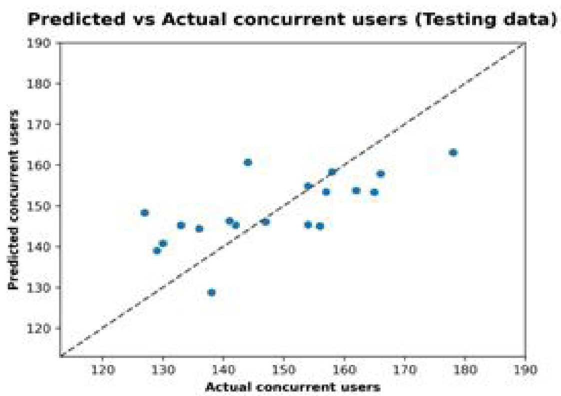

Figure 6: Support Vector Regression concurrent users (Testing data)

Figure 6 The Support Vector Regression (SVR) model demonstrates robust predictive capability for concurrent users, as validated by the test data in An R^2 of 0.473 represents a substantial improvement over linear regression, explaining nearly half the data variance. The model generalizes exceptionally well, evidenced by slightly superior test error metrics (RMSE: 10.139, MAE: 8.672) compared to its training performance. This strong out-of-sample accuracy confirms that SVR effectively captures the underlying non-linear relationships, establishing it as a reliable and superior predictor for forecasting concurrent user loads.

AdaBoost Regression

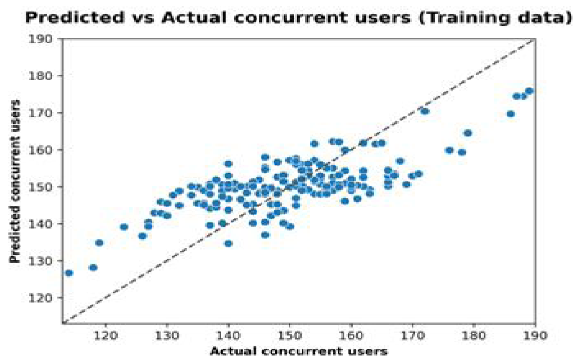

Figure 7: AdaBoost Regression concurrent users (Training data)

Figure 7 The AdaBoost model for predicting concurrent users is failing critically due to severe over fitting. While it captures some patterns in the training data (explaining ~49% of the variance), its performance plummets on unseen test data (explaining only ~11%). This is confirmed by error metrics; for instance, the Mean Absolute Error nearly doubles. The drastic performance gap indicates the model has memorized the noise and specifics of the training set rather than learning the underlying generalizable relationship. Consequently, it is unreliable for practical prediction and requires fundamental adjustments, such as tuning hyper parameters, reducing model complexity, or employing different validation techniques to improve its generalization.

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Table 4. Performance Metrics of Linear Regression concurrent users (Training Data and Testing Data)										
Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	SVR	Support Vector Regression	0.349	0.349	109.803	10.479	7.722	37.304	0.005	6.198
Test	SVR	Support Vector Regression	0.473	0.473	102.801	10.139	8.672	21.258	0.005	8.513

Table 4 demonstrates that the Support Vector Regression (SVR) model offers a substantial improvement in forecasting concurrent users, significantly outperforming linear regression. With a test R^2 of 0.473, it accounts for nearly half the data variance. Its exceptional generalization is evidenced by test errors (RMSE: 10.139) that marginally outperform the training metrics. This robust out-of-sample performance confirms SVR's superior capacity to model the underlying non-linear relationships, establishing it as a reliable solution for predicting user loads where simpler linear models prove insufficient.

Table 5. Performance Metrics of AdaBoost Regression concurrent users (Training Data and Testing Data)										
Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	ABR	AdaBoost Regression	0.491	0.493	85.822	9.264	7.850	18.703	0.004	7.262
Test	ABR	AdaBoost Regression	0.112	0.134	173.225	13.162	11.730	25.581	0.008	10.856

Table 5 the AdaBoost regression model predicting simultaneous user's exhibits significant over fitting and poor generalization. The model's performance on the test data deteriorates sharply. Its explanatory power, as indicated by the R^2 score, decreases from 0.491 (training) to 0.112 (test). All error metrics deteriorate significantly; for example, the RMSE increases from 9.264 to 13.162, and the MAE rises from 7.850 to 11.730. This wide performance gap confirms that the model has memorized the training data patterns without learning the underlying trend, making it an unreliable predictor of new, unseen data.

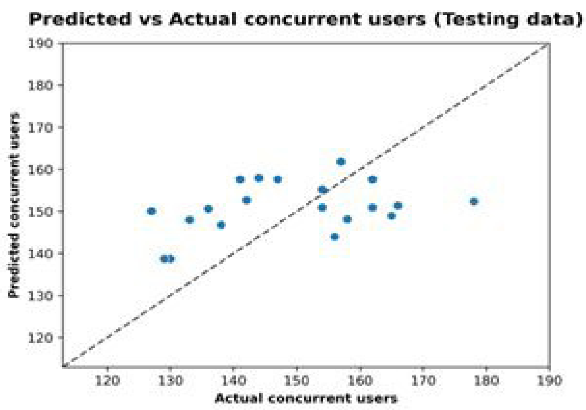

Figure 8: AdaBoost Regression concurrent users (Testing data)

Conclusion

The findings demonstrate that effective AI-driven personalization extends far beyond technical optimization; it represents a strategic necessity for achieving sustainable competitive advantage and brand differentiation in today's highly competitive digital marketplace. Empirical analysis of performance metrics identifies cache optimization as a crucial determinant of system reliability, revealing strong inverse relationships between cache hit rate, query latency, and service level objective (SLO) violation rate. Conversely, the pronounced over fitting observed in the AdaBoost models underscores the necessity of prudent model selection, feature engineering, and hyper parameter tuning when deploying AI systems in real-world production environments. The study emphasizes that a successful AI personalization framework requires cross-disciplinary collaboration among engineering, marketing, and data management teams. Such cooperation ensures not only technical resilience but also ethical transparency in algorithmic decision-making. Organizations are encouraged to invest in scalable data infrastructures, efficient model management systems, and continuous feedback mechanisms that iteratively refine personalization accuracy. Future research should focus on the development of advanced ensemble learning methods, intelligent caching strategies, and a deeper examination of the ethical implications surrounding hyper-personalized digital experiences. Ultimately, the seamless integration of site reliability engineering principles with intelligent personalization algorithms establishes a robust foundation for delivering superior user experiences. Such integration enhances engagement, satisfaction, and long-term customer loyalty—key determinants of success in the evolving landscape of modern e-commerce.

References

1. Raji, Mustafa Ayobami, Hameedat Bukola Olodo, Timothy Tolulope Oke, Wilhelmina Afua Addy, Onyeka Chrisanctus Ofodile, and Adedoyin Tolulope Oyewole. "E-commerce and consumer behavior: A review of AI-powered personalization and market trends." GSC advanced research and reviews 18, no. 3 (2024): 066-077.

2. Haider, Raiyan, Md Farhan Abrar Ibne Bari, Md Farhan Israk Shaif, and Mushfiqur Rahman. "Engineering hyper-personalization: Software challenges and brand performance in AI-driven digital marketing management: An empirical study." International Journal of Science and Research Archive 15, no. 2 (2025): 1122-1141.

3. Katkeri, Akshitha, E. V. Revathi, and S. Nithin. "A Cloud-Based Personalized E-Book Platform with AI-Driven Recommendations." Authorea Preprints (2025).

4. Moeini, M., A. Broumandnia, and M. Moradi. "A Personalized Web Recommendation System Based on a Weighted user Behavior Profile by Applying Extended Learning Method." (2025): 871-893..

5. Huang, Ying, Hong-Yu Zhang, and Jian-Qiang Wang. "A comprehensive mechanism for hotel recommendation to achieve personalized search engine." Journal of Intelligent & Fuzzy Systems 35, no. 3 (2018): 3733-3745.

6. Hermans, Liesbeth, and Maurice Vergeer. "Personalization in e-campaigning: A cross-national comparison of personalization strategies used on candidate websites of 17 countries in EP elections 2009." New media & society 15, no. 1 (2013): 72-92.

7. Sridhar Kakulavaram. (2022). Life Insurance Customer Prediction and Sustainbility Analysis Using Machine Learning Techniques.

Citation: Divya Soundarapandian (2025). Machine Learning Algorithms for Optimizing Search Personalization and Site Reliability in E-Commerce Platforms A Comparative Analysis of Linear Regression, SVR, and AdaBoost. International Journal of Artificial intelligence and Machine Learning, 3(3), 1-7. https://doi.org/10.55124/jaim.v3i3.286

International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 390 –. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/7649

8. Matthews, Paul, and Clemence Rhodes-Maquaire. "Personalisation and recommendation for mental health apps: a scoping review." Behaviour & Information Technology 44, no. 10 (2025): 2389-2404.

9. Deepta, C. S., R. Kaviya, and N. Sivakumar. "Enhancing E-Commerce with Personalized Product Recommendations." (2024).

10. PK Kanumarlapudi. (2024) Improving Data Governance with Advanced trade-off-Based Decision Models: A Comparative

11. Analysis of Open Data Platform Implementations in Multiple Domains. SOJ Mater Sci Eng 10(2): 1-6. DOI: 10.15226/2473-3032/10/2/00183

12. Bok, Sun Khi. "Enhancing User Experience in E-Commerce through Personalization Algorithms." (2023).

13. Paiu, Raluca. "Exploiting tag information for search and personalization." (2009).Montgomery, Alan L., and Michael D. Smith. "Prospects for Personalization on the Internet." Journal of Interactive Marketing 23, no. 2 (2009): 130-137.

14. Zheng, Zibin, and Michael R. Lyu. "Personalized reliability prediction of web service

15. zs." ACM Transactions on Software Engineering and Methodology (TOSEM) 22, no. 2 (2013): 1-25.

16. Leung, Kenneth Wai-Ting, Dik Lun Lee, and Wang-Chien Lee. "Personalized web search with location preferences." In 2010 IEEE 26th International Conference on Data Engineering (ICDE 2010), pp. 701-712. IEEE, 2010.

17. Desai, Darshana, and S. Kumar. "A study of design aspects of web personalization for online users in India." Corpus ID 64977506 (2017).

18. Peram, S. R (2023). Advanced Network Traffic Visualization and Anomaly Detection Using PCA-MDS Integration and Histogram Gradient Boosting Regression. Journal of Artificial Intelligence and Machine Learning, 1(3), 281. https://doi.org/10.55124/jaim.v1i3.281

19. Raji, Mustafa Ayobami, Hameedat Bukola Olodo, Timothy Tolulope Oke, Wilhelmina Afua Addy, Onyeka Chrisanctus Ofodile, and Adedoyin Tolulope Oyewole. "E-commerce and consumer behavior: A review of AI-powered personalization and market trends." GSC advanced research and reviews 18, no. 3 (2024): 066-077.

20. Bernacki, Matthew L., Meghan J. Greene, and Nikki G. Lobczowski. "A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose (s)?." Educational Psychology Review 33, no. 4 (2021): 1675-1715.

21. Van Hoof, Marieke, Damian Trilling, Judith Moeller, and Corine S. Meppelink. "It matters how you google it? Using agent-based testing to assess the impact of user choices in search queries and algorithmic personalization on political Google Search results." Journal of Computer-Mediated Communication 29, no. 6 (2024): zmae020.

22. Katkeri, Akshitha, E. V. Revathi, and S. Nithin. "A Cloud-Based Personalized E-Book Platform with AI-Driven Recommendations." Authorea Preprints (2025).

23. 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

24. Kakulavaram, S. R. (2023). Performance Measurement of Test Management Roles in 'A' Group through the TOPSIS Strategy. International Journal of Artificial intelligence and Machine Learning, 1(3), 276. https://doi.org/10.55124/jaim.v1i3.276

25. Wu, Chuhan, Fangzhao Wu, Yongfeng Huang, and Xing Xie. "Personalized news recommendation: Methods and challenges." ACM Transactions on Information Systems 41, no. 1 (2023): 1-50.

26. Abdullah, Noryusliza, and Rosziati Ibrahim. "Semantic web search engine using ontology, clustering and personalization techniques." In International Conference on Computational Science and Its Applications, pp. 364-378. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012.

27. Raghavendra Sunku. (2023). AI-Powered Data Warehouse: Revolutionizing Cloud Storage Performance through Machine Learning Optimization. International Journal of Artificial intelligence and Machine Learning, 1(3), 278. https://doi.org/10.55124/jaim.v1i3.278

Citation: Divya Soundarapandian (2025). Machine Learning Algorithms for Optimizing Search Personalization and Site Reliability in E-Commerce Platforms A Comparative Analysis of Linear Regression, SVR, and AdaBoost. International Journal of Artificial intelligence and Machine Learning, 3(3), 1-7. https://doi.org/10.55124/jaim.v3i3.286