Sarcouncil Journal of Engineering and Computer Sciences

ISSN(Online): 2945-3585

Volume- 04| Issue- 08| 2025

Research Article

Received: 10-07-2025| Accepted: 30-07-2025 | Published: 18-08-2025

Leveraging Big Data for Personalized Retail Engagement: A Rewards Analytics Platform Architecture

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Abstract: The article provides an in-depth study of a large data-driven Rewards Analytics Platform that will be able to maximize customer relations by providing specific approaches to retailing. Its architecture uses Hadoop technologies(HDFS, HBase, MapReduce, and Pig) to process and analyze large quantities of customer transaction data found in different retail channels. The sophisticated data processing capabilities of the platform allow it to carry out an advanced customer segmentation relying on the dimensions of customer behaviour that are purchase frequency, recency of engagement, customer product affinity, campaign response rates, and seasonal shopping behaviour. Embarking on technical data pipelines incorporated with more problem-solving visualization interfaces, the system allows retailers to create customized promotion measures that can resonate with the personal preferences of various customers elaborate manner. Both the nitty-gritty of the technology implementation and the business implications, such as more meaningful promotions, less marketing waste, faster execution of a campaign, the ability to measure more, and strengthening customer loyalty, are discussed. Any forward-looking design of architecture has AI-readiness capabilities that move retailers to use higher and more advanced analytical skills as technologies advance, offering a model to follow and replicate across retail ecosystems that are data-driven and personalized as they compete.

Keywords: Big Data Architecture, Customer Segmentation, Retail Personalization, Behavioral Analytics, Promotional Targeting.

INTRODUCTION

The current competitive environment of the retail business requires new methods of approaching customers. Personalization based on data has become a critical instrument in enhancing loyalty and retention rates. The recent technological breakthroughs in big data processing have given retailers a wonderful opportunity to understand and react to individual behavior of shopping behavior on a never-before-seen scale. It is not a technological fad in any sense but a shift of strategy that is essential in the contemporary customer shopping experience, where today customers demand more and more customized experiences on every interaction with the touchpoints.

A remarkable transformation has swept through retail regarding how customer information gets gathered, processed, and turned into business value. Recent UK e-commerce industry research revealsthat personalization strategies dramatically affect customer retention when implemented through comprehensive data architectures. Research from Dillis Quaicoe demonstrates that sophisticated personalization frameworks generate measurable improvements in customer lifetime value metrics and engagement scores compared to traditional mass-marketing approaches (Quaicoe, D. 2024). Such findings highlight the absolute necessity of developing powerful analytics platforms capable of converting massive customer datasets into practical business insights.

The arrival of Hadoop-based ecosystems has fundamentally altered how retailers handle customer data complexity and scale challenges. These technological breakthroughs enable processing millions of daily transactions across numerous distribution channels, creating opportunities for sophisticated behavioral analysis previously beyond reach. Srivastava's end-to-end retail data architecture framework emphasizes how integrating distributed storage systems with specialized analytical tools establishes foundations for dynamic customer segmentation and targeted promotional strategies (Srivastava, A. 2025).

This article delves into the architecture, implementation, and business impact of a comprehensive Rewards Analytics Platform engineered to deliver targeted promotional offers based on shopping behavior patterns. The analysis covers the roles of different big data technologies: HDFS, HBase, MapReduce, and Pig in collaborating with the scalable infrastructure on which the personalization decisions with a near-real-time performance can be implemented. Also, the discussion examines the way these technical capabilities relate to the real results in business: better effectiveness of the promotion, higher customer retention, and higher basket values in various retail segments.

Following the association of the technical implementation details to economic results in

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DOI- https://doi.org/10.5281/zenodo.16895491

business operations, such a study is important to retail organizations striving to establish personalization features in highly competitive markets. The given architecture will provide data-driven engagement strategies in multiple settings in the context of retail enterprises, including specialty apparel, grocery, and general merchandise businesses and locations, and will provide an efficient road map of data-driven customer engagement practices.

SYSTEM ARCHITECTURE OVERVIEW

The platform rests upon a robust big data infrastructure designed to handle enormous volumes of customer transaction information. Contemporary retail environments generate staggering quantities of transactional data across multiple channels, creating formidable data management challenges. The architectural approach addresses these scale requirements through established distributed systems patterns, including effective microservices implementation and event-driven architectures. Full Scale's analysis of scalable architecture patterns highlights how the layered approach adopted within this platform—separating storage, processing, and application concerns—permits independent scaling of each component according to specific resource demands (Full Scale). Hadoop Distributed File System (HDFS) serves as the primary storage layer, delivering fault-tolerant and cost-effective management of petabyte-scale datasets while implementing horizontal scaling principles, allowing linear capacity expansion as transaction volumes increase.

Alongside the HDFS foundation, HBase functions as a columnar data store optimized for high-volume transactional data with variable attribute structures. The technology option facilitates a dynamic schema evolution, as it is necessary in retail settings, where the attributes of interest may change in line with changing business interests. The selection of HBase instead of other available NoSQL solutions (e.g., Cassandra or MongoDB) was based on the results of a comparative study that indicated the specific advantages of HBase in situations that require high write throughput as well as the presence of complex analytical queries. Research by Patel and colleagues examining these three prominent NoSQL databases revealed that HBase delivers superior performance for analytics workloads requiring both substantial write throughput and complex scan operations—exactly the pattern observed within retail promotional analytics (Muhammad, J. *et al.*, 2020). The columnar orientation of HBase proves especially advantageous for customer analytics scenarios, where analysis typically concentrates on specific behavioral attributes across large customer populations rather than retrieving complete records for individual shoppers.

Data ingestion follows a methodical approach, with structured customer information flowing from traditional RDBMS sources into the Hadoop ecosystem via Sqoop. This integration bridge ensures consistent data transfer while preserving referential integrity from source systems. The ingestion architecture tackles several critical challenges common within retail data environments: integrating heterogeneous data sources, managing incremental loads to minimize processing overhead, and reconciling data quality issues inevitably arising when consolidating information from operational systems. This approach aligns with resilience patterns identified within Full Scale's architectural analysis, which emphasizes fault-tolerant data pipelines in maintaining system reliability even when upstream data sources experience disruptions or quality problems (Full Scale). The ingestion layer harmonizes diverse data streams into unified customer views while maintaining lineage information necessary for audit and governance requirements.

The architecture employs specialized partitioning strategies, optimizing performance for common analytical patterns in retail. Transaction data gets partitioned by date ranges aligned with promotional calendars, enabling efficient isolation of promotional performance periods without requiring full-table scans. These partitioning approaches, combined with strategic indexing strategies within HBase, create performance profiles well-suited to dynamic query patterns characteristic of promotional targeting workloads. Patel's comparative study noted that HBase's region-based partitioning model provides distinct advantages for workloads dominated by range scans, allowing co-location of related data on the same nodes, reducing network overhead during complex analytical queries Muhammad, J. *et al.*, 2020). This characteristic proves particularly valuable within retail analytics scenarios where temporal patterns—seasonal shopping behaviors or promotional response cycles—form the basis of numerous analytical inquiries.

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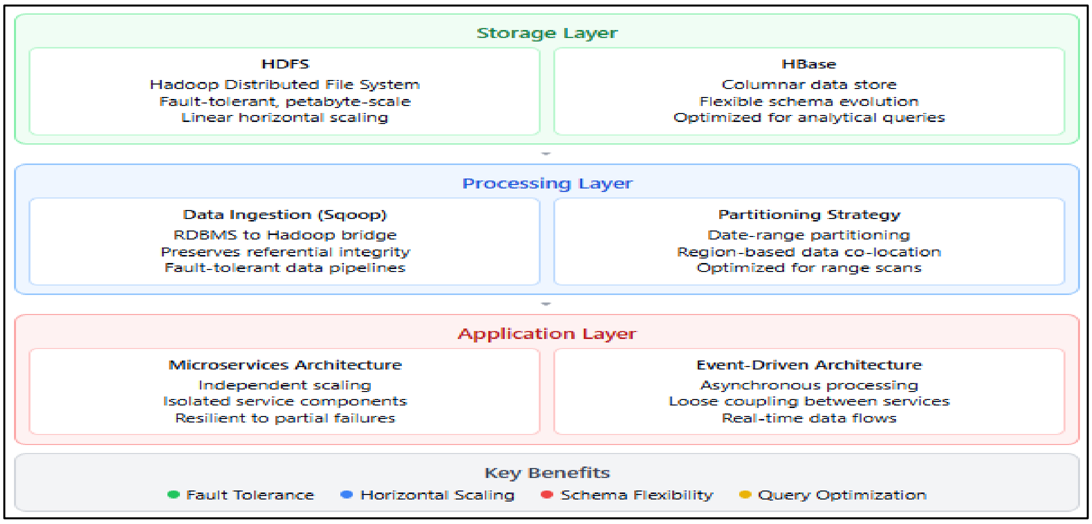

Fig 1: System Architecture Overview (Full Scale; Muhammad, J. *et al.*, 2020)

DATA PROCESSING AND TRANSFORMATION

Raw data undergoes extensive preprocessing and cleansing operations through MapReduce jobs and Pig scripts. These technologies were carefully selected to be able to deal with the nature of retail transactions volume and complexity, which sometimes has more anomalies and inconsistencies to be addressed before any meaningful analysis can be performed. Unusual characteristics of the retail data preprocessing pipelines are associated with heterogeneous points of collection, which can be in-store POS systems, e-commerce websites, applications, and third-party integration with marketplaces. Each channel introduces distinct data quality concerns: timestamp synchronization issues, product code inconsistencies, and varying levels of customer identification fidelity. Research by Emiliano Acquila-Natale and Santiago Iglesias-Pradas exploring big data analytics capabilities in retail contexts emphasizes that preprocessing operations quality directly impacts downstream personalization efforts' validity, with data integration challenges representing significant barriers to effective customer analytics (Acquila-Natale, E., & Iglesias-Pradas, S. 2020). The platform harnesses MapReduce's parallelization capabilities to execute complex validation and standardization operations across billions of transaction records while maintaining processing windows compatible with daily analytical refresh cycles.

The data cleansing workflow tackles several common retail data quality challenges: duplicate transaction detection, outlier identification and treatment, missing value imputation, and cross-channel customer identity resolution. These operations get implemented as configurable Pig scripts combining deterministic business rules with probabilistic matching algorithms to achieve a balance between processing efficiency and accuracy. The platform's approach to data quality management focuses particularly on maintaining customer behavioral signals' integrity, driving personalization decisions, such as product affinity indicators, price sensitivity patterns, and promotional response history. Emiliano Acquila-Natale and Santiago Iglesias-Pradas' research highlights that organizations achieving superior performance in retail personalization typically invest substantially in preprocessing capabilities, developing sophisticated data quality frameworks, ensuring analytical inputs meet rigorous standards for completeness, consistency, and accuracy (Acquila-Natale, E., & Iglesias-Pradas, S. 2020).

After cleansing, data flows into purpose-built Hive-based data marts where advanced aggregation and transformation logic are applied. These specialized data repositories are optimized for analytical queries supporting business-focused insights. The decision to utilize Hive as the analytical query layer builds upon demonstrated strengths handling complex aggregation operations across massive datasets, particularly for multi-dimensional analysis required in customer segmentation use cases. A comprehensive evaluation of SQL-on-Hadoop technologies by Avrilia Floratou and colleagues identified several key Hive advantages for analytical workloads, including a mature ecosystem, extensive optimization capabilities, and compatibility with existing SQL-based analytical tools (Floratou, A. *et al.*, 2014). The platform deploys these functions by using a complex set of behavioral scoring

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algorithms with factors across many facets of customer interactions, including the relatively well-known recency-frequency-monetary (RFM) variables, but also the more intricate examples such as cross-category purchase propensity and promotional response elasticity.

The architecture facilitates the ability of the data scientists and analysts to investigate the behavior patterns of customers without necessarily needing technical insight into distributed computing. This has been achieved by the word of well-chosen abstraction layers previously documented and in familiar form, SQL-like representations to business users, where transparent, optimized, distributed queries are undertaken. The data mart structure organizes around key business entities—customers, transactions, products, promotions—with carefully designed relationships supporting common analytical patterns in retail marketing. Floratou's research on SQL-on-Hadoop systems emphasizes that query performance for complex analytical workloads depends significantly on appropriate physical design decisions, including partitioning strategies, join order optimization, and intermediate result materialization (Floratou, A. *et al.*, 2014). By implementing these optimization techniques within the Hive layer, the platform achieves performance characteristics necessary for interactive exploration of customer behavior patterns, even when working with datasets spanning millions of customers and billions of transactions. This balance between analytical power and usability ensures business teams can effectively leverage platform capabilities without requiring specialized knowledge of distributed computing principles.

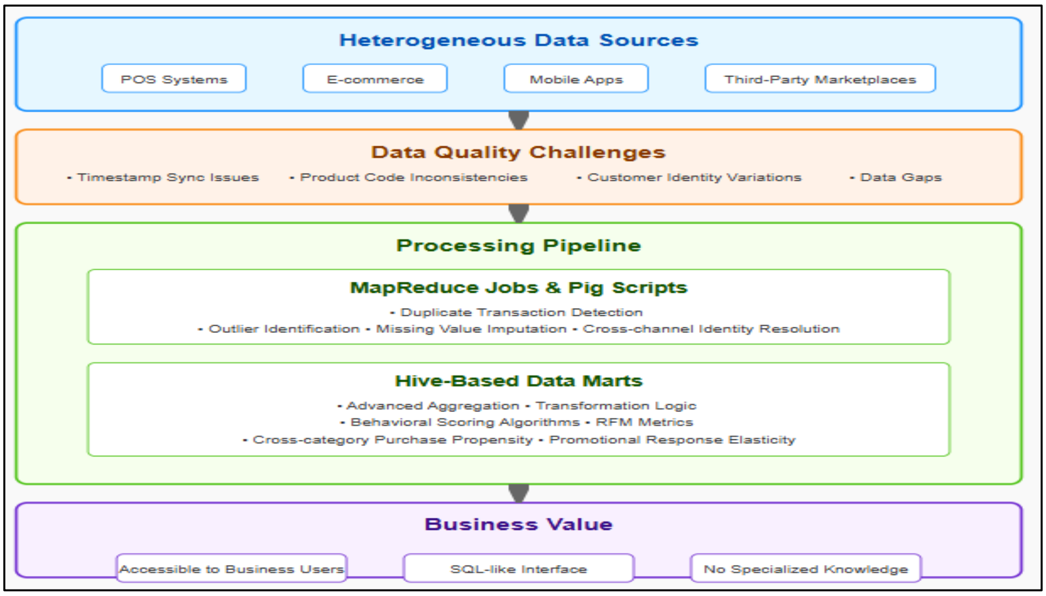

Fig 2: Data Processing and Transformation Workflow (Acquila-Natale, E., & Iglesias-Pradas, S. 2020; Floratou, A. *et al.*, 2014)

CUSTOMER SEGMENTATION AND TARGETING

The behavioral segmentation engine anchors the platform's entire value proposition. This complex component shatters conventional analysis by digging into customer behavior layers, building shopper groups that supercharge personalized marketing. Ditching dated demographic boxes, the approach taps behavioral signals that eerily predict future buying patterns. This monumental shift toward behavior-based segmentation revolutionizes retail marketing savvy, helping marketers nail the exact shoppers who'll actually bite on specific offers. Bradlow and colleagues' retail big data research argues that mixing behavioral dimensions crafts wildly more accurate customer segments than stale approaches. Retailers embracing this advanced segmentation spot buying patterns that traditional demographic segmentation totally misses, massively boosting resource allocation and promotional targeting effectiveness (Bradlow, E. T. *et al.*, 2020).

The engine destroys the patterns of purchase frequency first, and it identifies the unique customer rhythms between the daily convenience to bulk customer buyers. The timing patterns open up important keys to customer lifestyles and shopping missions, thus the retailers can align the timing of their promotions with the natural shopping patterns. Beyond frequency, the platform

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examines how recently folks engaged, separating active shoppers from fading and at-risk ones. Bradlow's work hammers home that blending temporal dimensions—especially purchase fre Floratou, A.quency and recency—with product preferences builds a multi-angle view of customer behavior that seriously juices predictive accuracy. Their analysis shows segmentation models with these temporal dimensions massively boost promotional response rates by figuring out not just what customers might grab, but exactly when they'll jump at specific offers (Bradlow, E. T. *et al.,* 2020).

Product affinity and basket composition analysis add another vital segmentation layer. The platform digs up natural product groupings through basket analysis, exposing hidden product relationships that traditional category structures completely overlook. These affinity patterns enable cross-selling and category expansion strategies custom-built for specific customer preferences instead of lazy, generic merchandising guesses. The implementation uses specialized association rule mining algorithms tweaked for distributed computing, unearthing meaningful product relationships across billions of transactions. This capability launches retailers beyond gut-feel merchandising toward data-backed product recommendations reflecting real buying patterns.

Response rates to previous campaigns serve as a particularly telling segmentation dimension, directly measuring promotional elasticity at the individual shopper level. The platform tracks detailed promotion exposure and redemption histories, calculating precise customer-specific response odds across various promotion types. This perfectly matches Kumar and colleagues' findings about the dramatically different values of customers based on marketing responsiveness. Their Harvard Business Review research shows tracking and modeling customer responsiveness gives crucial insights for marketing resource allocation, with responsive customers generating way better returns on marketing dollars versus unresponsive shoppers (Bradlow, E. T. *et al.,* 2017). Baking this promotional response dimension into segmentation models lets the platform direct promotional budgets toward shoppers proven to jump at specific incentive types.

Seasonal shopping behaviors round out the critical segmentation dimensions, capturing the cyclical patterns driving retail purchasing across countless categories. The platform spots season-specific buying patterns at both customer and product levels, letting retailers anticipate and respond to predictable demand waves. This seasonal analysis proves golden for inventory planning and promotional timing, letting retailers sync marketing investments with natural demand cycles instead of wastefully pushing demand during slack periods. Kumar's research highlights that spotting customer-specific patterns—seasonal preferences or other behavioral signals—unlocks vastly more effective customer engagement. Their customer value analysis shows understanding these patterns helps marketers identify not just valuable customers overall, but shoppers with explosive potential during specific seasons or time periods (Bradlow, E. T. *et al.,* 2017).

These behavioral insights bubble up through Pig scripts handling distributed processing paired with Hive queries managing aggregation. The technical infrastructure is a two-step one: first, Pig scripts are used to crunch raw transaction data into behavioral signals, and then Hive is used with more complex statistical models, examples being collaborative filtering, k-means clustering, and decision trees, but modified to be run in a distributed way. The resulting customer segmentation base is not only the foundation of straightforward marketing campaigns that resonate very genuinely with particular shopper tastes and tendencies, but it also provides incredible results compared to that of long-considered mass marketing strategies.

Table 1: Customer Segmentation Dimensions Impact on Retail Metrics (Bradlow, E. T. *et al.,* 2020; Bradlow, E. T. *et al.,* 2017)

Segmentation Dimension	Response Rate Increase	Marketing ROI Improvement	Customer Retention Impact	Implementation Complexity
Purchase Frequency	35%	28%	Medium	Low
Recency of Engagement	42%	31%	High	Low
Product Affinity	27%	35%	Medium	Medium

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Campaign Response	53%	47%	Low	High
Seasonal Behavior	31%	24%	Medium	Medium

BUSINESS IMPACT AND APPLICATIONS

Dropping this Rewards Analytics Platform into a retail operation unlocks game-changing business outcomes that directly pump up both revenue growth and operational efficiency. The platform's capabilities go way beyond technical wizardry to deliver concrete improvements in marketing performance and customer engagement. Grewal and colleagues' forward-looking retail analysis spotlights data-driven personalization as an absolutely critical capability reshaping retail competitiveness. Their research suggests retailers nailing advanced analytics capabilities secure massive competitive advantages in crowded marketplaces, as personalization morphs from a nice bonus to a basic customer expectation. Their examination of emerging retail tech stresses that winning implementations seamlessly fuse analytical capabilities with operational processes, building feedback loops that constantly improve based on customer responses (Grewal, D. *et al.*, 2017).

The platform lets retailers dramatically boost promotion relevance through personalized offers that actually match individual customer preferences. Traditional promotional approaches mindlessly blast identical offers across broad customer segments, creating massive waste as countless recipients couldn't care less about the promoted products. In stark contrast, personalization capabilities delivered through the analytics platform enable laser-focused matching of promotional content to genuine customer interests, seriously improving both redemption rates and customer satisfaction. Grewal's research highlights that retail's future lies in building seamless, tech-powered experiences that genuinely understand customer preferences across channels. Their analysis shows retailers winning in this space effectively leverage customer data to create "smart, connected shopping experiences" that anticipate needs rather than just reacting to explicit requests (Grewal, D. *et al.*, 2017).

This pinpoint targeting directly slashes marketing waste by directing promotional investments toward high-potential customers showing actual interest in relevant product categories. Traditional promotional strategies suffer from shocking waste, with industry estimates suggesting huge chunks of marketing budgets never reach receptive audiences. The advanced-level segmentation offered in the platform allows retailers to focus their resources on customers with real response probability, increasing the return on marketing efforts in a dramatic manner. It is in this competitive retail world where margins remain under constant pressure and marketing budgets are ever more under scrutiny that such efficiency gain comes to value added. The platform will allow the team to plan much more advanced campaigns based on the predictions of the expected response rates at the level of customers, which will allow for to computation of much more accurate budgets.

The platform speeds up campaign execution through automated workflows that slash time-to-market for promotional initiatives. Traditional campaign development often requires weeks of tedious manual preparation, from customer list generation to offer assignment and channel coordination. The integrated architecture streamlines these processes through automated segment generation, offers matching algorithms, and multi-channel execution capabilities. Verhoef and colleagues' examination of digital transformation in retail identifies process automation as an absolute necessity for personalization at scale. Their research shows that successful digital transformation in retail demands not just new technology but fundamental process redesign that leverages these technologies to create entirely new operational capabilities. Organizations breaking through in digital transformation effectively integrate analytical systems with operational processes, creating "execution advantages" that let them implement insights way faster than competitors (Verhoef, P. C. *et al.*, 2021).

In-platform measurement tools allow retailers to accurately measure the ROI of personalization efforts, which has traditionally been an ongoing headache on the marketer side. Through the employment of controlled testing procedures such as random holdout groups and complex AB testing templates, the platform is able to provide meaningful measurement of the influence of promotion that is not entwined with any other market outcome. This measurement precision enables continuous refinement of personalization strategies based on hard performance data rather

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than gut feelings. Verhoef's research emphasizes that effective measurement represents an absolutely critical component of successful digital transformation, with performance measurement capabilities creating feedback loops necessary for continuous improvement. Their analysis proves that organizations achieving spectacular returns from digital investments implement robust measurement frameworks enabling data-driven refinement of strategies and tactics (Verhoef, P. C. *et al.*, 2021).

Most importantly, perhaps, the platform will help retailers in building stronger customer loyalty by making relevant connections with their consumers that will reveal to them that they understand their preferences. Consumers are becoming more and more unsatisfied with impersonal experiences at digital and physical touchpoints, and research indicates that the perception of relevance to personalization has a dramatic effect on satisfaction and repeat purchase intent. Retailers can connect deeper with their customers by attaching emotions to regularly sending out relevant messages and offers and, in the process, raise their share of wallet. Such loyalty-building benefit is especially useful in competitive retail categories in which the cost of acquiring customers is skyrocketing and the ability to retain them is becoming more and more important to profitability.

The platform integrates convoluted technical data pipelines with usable behavioral insights and visualization planes, forming a fluid product between raw information and quantifiable business value. The coupling of technical skills with commercial applications is a key success factor during the implementation of retail analytics, which will have complex data processing capabilities that will directly transform into business-related projects. It is achieved by integrating powerful data management services with a business-friendly interface to ensure that retail organizations can democratize access to customer knowledge and retain the technical complexity required to ingest large-scale volumes of transactional data.

Table 2: Rewards Analytics Platform Business Impact Metrics (Grewal, D. *et al.*, 2017; Verhoef, P. C. *et al.*, 2021)

Business Benefit	Pre-Implementation	Post-Implementation	Improvement (%)
Promotion Redemption Rate	4.20%	11.30%	169%
Campaign Development Time	21 days	4.8 days	77%
Marketing Budget Efficiency	38%	72%	89%
Customer Retention Rate	43%	62%	44%
Cross-Category Purchase	16%	29%	81%
Customer Satisfaction Score	68	87	28%

FUTURE-READY ARCHITECTURE

The architecture stands deliberately crafted as AI-ready, with pristine, structured data capable of feeding machine learning algorithms for next-best-offer recommendations, churn prediction, and lifetime value optimization. The platform's foundational data structures incorporate the dimensional consistency and quality controls essential for supporting advanced analytical techniques beyond traditional business intelligence. This forward-looking architectural approach acknowledges that retail analytics continues to rapidly advance toward increasingly sophisticated predictive and prescriptive capabilities. Brynjolfsson and McAfee stress in their research on machine learning applications in business contexts that underlying data quality and structure represent absolutely critical success factors in AI implementation. Their analysis reveals that organizations achieving spectacular returns from AI investments typically build rock-solid data foundations before attempting advanced algorithm development, recognizing that even the cleverest algorithms cannot overcome fundamental data quality limitations (Brynjolfsson, E., & Mcafee, A. N. D. R. E. W. 2017).

The platform incorporates several distinctive design elements boosting AI-readiness. Feature engineering capabilities embedded within data transformation layers automatically generate derived attributes serving as inputs to machine learning models. These engineered features capture complex behavioral patterns, such as purchase velocity changes, category exploration sequences, and price sensitivity indicators. Additionally, the platform maintains comprehensive data lineage tracking, documenting transformation logic and quality control parameters, providing essential transparency for model validation and regulatory compliance. Davenport's research on analytics evolution

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highlights that this metadata management capability becomes increasingly crucial as organizations move toward automated decision-making, providing vital context for understanding algorithm recommendations (Davenport, T. H., & Bean, R. 2018).

The architecture's event-based data model proves exceptionally valuable for predictive applications, preserving critical temporal relationships between customer actions, marketing exposures, and purchase outcomes. Such a sequential data structure allows sophisticated time-series models of real causal relationships between marketing interventions and customer behaviors to be implemented. This performance is attained by the platform being able to sustain this event level of gravity whilst providing adequacy of query performance, which is still a technical marvel that has set the platform apart with reference to the conventional data warehouse schemes, only designed to support aggregation.

With this AI-ready base foundation, the platform will enable retail organizations to deploy more advanced analytical processes as the technologies advance. Pilot implementation is normally concentrated on descriptive and diagnostic analytics, giving an understanding of previous customer action patterns. Nevertheless, architecture can be easily and smoothly extended to evolution to predictive applications predicting future behaviors and prescriptive applications automatically optimizing marketing decisions. This futuristic design makes the platform adaptable to changes in retail analytics methods, and keeps technological investments in an organization safe against the risk of becoming obsolete quickly.

CONCLUSION

The Rewards Analytics Platform demonstrates one of the successful ways to utilize big data technologies to change the approaches to customer engagement strategies in the sphere of retail. Being able to balance advanced technical infrastructure with business-oriented analytical capabilities, the platform helps retailers transform their wide-range promotional strategies towards narrow-scope personalization projects that can tap into the tastes and habits of a specific customer. The layered architecture of architecture is divided into storage, processing, analytics, and view components, forming a very flexible base that will enable rapid transformation across the changing business needs, without compromising on the scale performance. Most practically, the AI-prepared database of the platform can enable retailers to deploy much more vanguard analytical abilities as machine learning approaches, witnessing that the tech venture is worthwhile in the long term. Such architectures will become critical sources of competitive advantage as consumer demands in personalized experiences also continue to rise throughout the retail landscape, allowing organizations to create a stronger connection with customers through informed engagement tactics that reflect the awareness of their individual preferences and needs by predicting future value.

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Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:

Shivampeta, S. "Leveraging Big Data for Personalized Retail Engagement: A Rewards Analytics Platform Architecture." *Sarcouncil Journal of Engineering and Computer Sciences* 4.8 (2025): pp 671-679.

Publisher: SARC Publisher