International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

AI-Powered Big Data Analytics for Smart Retail Customer Journey Optimization

Madhu Sathiri

Independent Researcher, India

sathirimac@gmail.com

ABSTRACT: Intensifying of competition among modern retail companies necessitates a transition from big data to enhanced intelligence through optimization of the still-unknown customer journey by means of artificial intelligence and business analytics. Such a transition calls for a rethinking of conceptual foundations and development of a data ecosystem. Data constitute a fundamental part of modern intelligent systems. The new-age retail environment produces tremendous amounts and varieties of data about customer experiences during their journey, both online and offline. A model-based customer-journey-mapping and touchpoint-optimization technique and its supporting architecture are presented. Other needed technologies encompass a wide spectrum of artificial intelligence techniques for machine learning, deep learning, and natural language processing. Regulatory and ethical aspects of the exploitation of such a data ecosystem support the smart retail business.

Customer journey mapping defines all stages of customer experience with a company or brand and includes its online and offline components. Every stage encompasses several touchpoints for customer experience assessment: awareness, consideration, intent, evaluation, purchase, consumption, and advocacy. For a comprehensive customer-journey model, advanced customer experience metrics are required in addition to those for each touchpoint: net promoter score, customer satisfaction score, customer lifetime value, customer engagement score, and customer effort score. All customer-journey metrics determine the optimization of touchpoint impact on profit.

KEYWORDS: Retail Analytics, Predictive Analytics, Customer Behavior, Personalization, Omnichannel Retail, Consumer Insights, Digital Retail Transformation, Data-Driven Decision Making, Customer Engagement, Retail Optimization, Experience Management, Intelligent Retail Systems, Consumer Journey Analytics, Retail Data Integration, AI-driven Marketing, Customer Lifetime Value, Retail Intelligence Platforms, Behavioral Analytics, Decision Support Systems, Retail Innovation.

I. INTRODUCTION

Despite research attesting to the superior predictive capability of AI-powered big-data analytics for product research and development, product assortment, pricing, promotion, location and channel strategies, inventory management, and websites, little progress has been made in optimising the customer journey in smart retail. AI-driven predictive analytics and machine-learning infrastructures require different sources, methods, and models compared with those for AI-development processes. Mapping and optimising the customer journey remains a critical challenge. Answers to two key questions are therefore vital to promote and support future investment in research, development, and implementation: What theories underpin AI-powered big-data analytics for optimising the customer journey? What data ecosystems are needed to enable developers and entrepreneurs to successfully implement AI-powered big-data analytics for optimising the customer journey?

Four interconnected theories are core to AI-driven and machine-learning predictive-analytics products and services: (1) data, (2) analytics, (3) intelligence, and (4) optimisation. In the context of smart retail, three further hypotheses focus specifically on mapping and optimising the customer journey: (1) effective mapping and analysis of the customer journey requires integration of multiple frameworks and models; (2) AI-powered big-data analytics must be capable of mapping the entire customer journey and optimising it across all functional areas; and (3) the effectiveness of customer-journey mapping and optimisation is best evaluated at the individual-journey level.

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

1.1. Overview of AI-Driven Transformation in Retail Analytics

AI technologies are penetrating every aspect of human society. Creating and developing smart environments is providing immense opportunities for improving human life while addressing major global challenges. Smart retail is one major area gaining attention, where the main objective is to transform the retail services by improving all key indicators according to customer expectations.

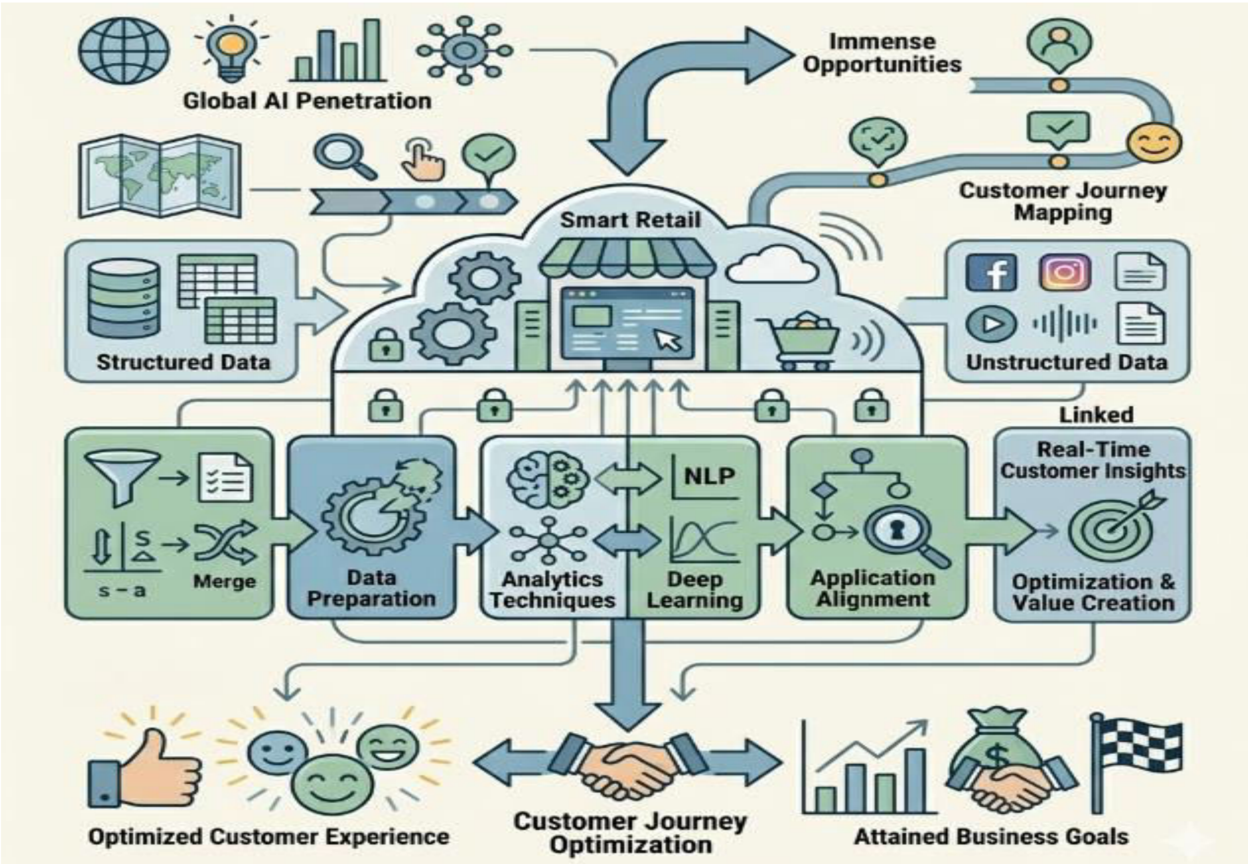


Fig 1: Optimizing the Smart Retail Customer Journey: An Interrelated Data and Analytics Ecosystem for Real-Time Insight Alignment

Research shows that real-time customer insights based on captured customer feedback and behavior generated along the entire customer journey and provided to the relevant decision-makers throughout the journey are among the main factors that can add value and improve success. These insights can be derived from vast amounts of structured and unstructured data by applying advanced data analytics techniques. The numerous techniques available include machine learning, deep learning, natural language processing, etc. Nevertheless, capturing, enhancing, preparing, merging, and processing the required data, used individually or in combination, in a timely manner in line with business requirements and objectives pose a significant challenge.

Although a major focus is advancement of technique performance, the big-area question is how to optimally utilize the most appropriate technique to derive the required findings for tailored applications with defined goals. How the customer experience can be optimized and business goals attained relies on ensuring that the analytics techniques applied address the real business needs. Based on the above observations and on the existing literature, comprehensive and interrelated data and analytics ecosystem models have been proposed that support customer journey mapping and optimization.

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

II. THEORETICAL FOUNDATIONS OF AI-DRIVEN ANALYTICS IN RETAIL

Data, analytics, intelligence, and optimization constitute the key theoretical cornerstones of innovative business intelligence approaches exploiting AI capabilities to transform the retail customer journey into a store of data accessible for AI-based data analytics purpose. Seamless integration with available AI-driven big data analytics technologies supports a more precise mapping of customer journey processes and facilitates the identification of the significant journey moments for journey optimization.

Existing theory and operational framework provide the basic ingredients for the proposed AI-optimized customer journey analytics model. In-depth scientific investigations of the retail customer journey process have resulted in a broad range of retail customer journey research hypotheses drawn from the customer journey mapping processes. The data analytics and optimization branches of intelligence and knowledge have been investigated and reflected in the framework that allows deep dive into detail in these domains. Translating an operational retail customer journey mapping matrix into process-oriented customer journey business intelligence requires preceding big data datafication of retail customer journey processes and touchpoints. Datafication of the retail customer journey is the process of utilizing data for business decisions and describes a dataset under the influence of a context in the process of collecting, processing, and storing.

Equation 1) Customer journey stages → funnel equations (counts + conversion)

1.1 Stage counts

Let:

- N_s = number of customers in stage s, where $s \in$ {Awr, Con, Int, Eval, Pur, Cons, Adv}

These counts come from event logs (impressions, visits, add-to-cart, checkout, repeat purchase, review/referral, etc.).

1.2 Stage-to-stage conversion rate (step-by-step)

From stage s to next stage $s+1$:

1. Define "converted" customers:

$$N_{s\to s+1} = N_{s+1}$$

(when stage counts are nested; i.e., everyone in $s+1$ must have passed through s)

2. Define conversion probability:

$$\mathrm{CR}_{s\to s+1} = \frac{N_{s\to s+1}}{N_s}$$

3. Substitute:

1.3 Overall funnel conversion (awareness → purchase)

1. Define:

$$\mathrm{CR}_{\mathrm{Awr}\to\mathrm{Pur}} = \frac{N_{\mathrm{Pur}}}{N_{\mathrm{Awr}}}$$

2. Or as product of step conversions:

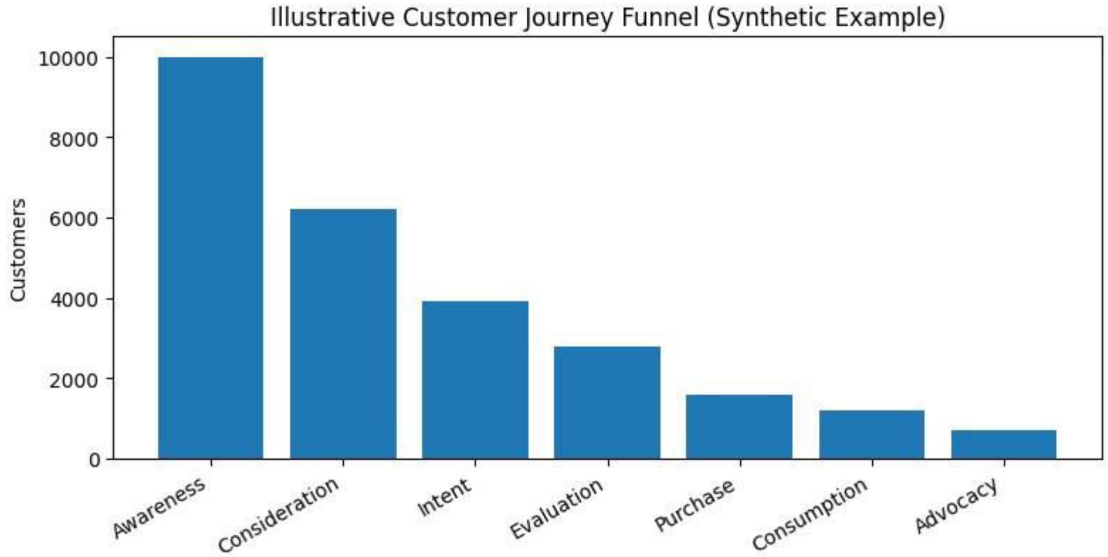
$$\mathrm{CR}_{\mathrm{Awr}\to\mathrm{Pur}} = \prod_{s=\mathrm{Awr}}^{\mathrm{Eval}} \frac{N_{s+1}}{N_s}$$

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030



2.1. Understanding the Role of AI in Transforming Retail Analytics

The contemporary retail landscape has evolved into a fast-paced and disruptive environment, characterized by hyper-concurrent customer interactions across multiple channels and devices. Retailers are increasingly hooking into these rich customer data streams sourced from the various customer engagement touchpoints through their digital and physical sales environments. Kesharwani (2022) argues that the integration and proper utilization of these huge data volumes can provide an organization with sustainable competitive advantages in terms of personalized marketing, improved customer service, efficient operations, and platform-based business strategies. Retailers thus need to define a robust Big Data-based analytic strategy to gain deeper customer insights, enhance future decision-making, and optimize all stages of the customer journey across the physical, digital, and social media channels.

A critical requirement for advancing such analytics within the complex Big Data retail ecosystem is the application of AI-driven concepts and techniques for optimizing the customer journey across the customer lifecycle. AI techniques such as machine and deep learning, natural language processing, and optimization are increasingly being used in customer journey mapping and optimization tasks. Retailers need to determine specific objectives for applying these advanced concepts, identify the appropriate AI technique for achieving the desired outcomes, and propose performance evaluation metrics.

III. DATA ECOSYSTEMS FOR SMART RETAIL

Smart retailing is enhanced by AI-powered intelligent data analysis, enabled by powerful analytical engines processing and analyzing rich data sourced from multi-layer smart data ecosystems. Intelligence is solidly based on data, and data from many different sources needs to meet established quality criteria and be suitably integrated to enable smart intelligence. The current chapter considers data sources for smart retailing intelligence, the integration architecture for these data sources, the required data quality parameters, and the requirements for interoperability between layer-level systems.

Smart retail intelligence is driven by numerous different data sources, spanning the entire customer journey and the back-end support operations of the retailer. These data sources include smart storefronts (for customer location and movement analysis), transaction processing, finished product quality examination, ICT-system-level and customer-service applications, as well as data generated during fulfilment and service delivery activities. The data generated at these different source points of the customer journey happen at different frequencies, at different time intervals, are of different types, and belong to different categories. Such diverse characteristics are expected to create serious challenges for aggregation of the data within the customer journey in data lake environments, unless the technical design architecture and governance framework clearly specify the data-acquisition frequency, complexity, consistency, and controllable factors associated with the data aggregators and enable data model design specific to the targeted analysis objective or hypothesis.

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

Metric	Illustrative value
NPS	27.00
CSAT (Top-2 box %)	67.00
CES (Ease %)	68.33
CLV (simple discounted, INR)	3155.20

3.1. Building Robust Data Ecosystems for Enhanced Retail Intelligence

Data-driven intelligence has gained considerable attention in the big data era, leading to the concept of the data revolution. Organizations are constantly striving to enhance their intelligence through the collection, integration, and analysis of various types of data for making better-informed decisions. Data ecosystems are crucial in achieving such intelligence. Data ecosystems are dynamic, evolving, and organized communities built around data that enable parties to share data for mutual benefits. Four components constitute dynamic data ecosystems: data entities, stakeholders, associated data and analytics, and technology

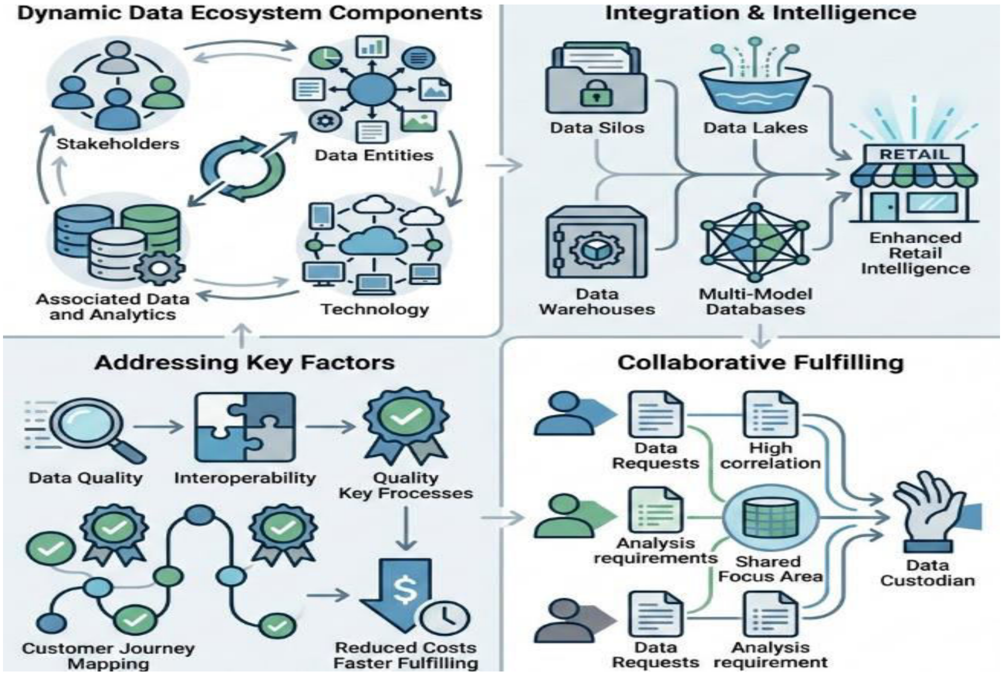


Fig 2: Optimizing Retail Intelligence within Dynamic Data Ecosystems: A Framework for Collaborative Data Integration and Correlated Request Fulfillment

Four main data integration architectures support analytic operations in retail settings, namely, data silos, data lakes, data warehouses, and multi-model databases. However, even with the necessary architecture for data integration, enhancing retail intelligence requires careful consideration of data quality, data interoperability, and data quality during the Customer Journey Mapping process. Improving data quality can also help organizations meet data requests more quickly and cheaply. In a collaborative environment, different business partners, with their proprietary data, may create their own focus area and discuss the associated data risk. It is common to see these partners articulate different types of analysis requests on the focus area, which can then lead to their parties requesting the same data for their separate analysis. Such data requests may have high correlation, and data custodians should consider grouping and fulfilling these requests together.

Stage	Customers	Stage conversion to next
Awareness	10000	0.6200
Consideration	6200	0.6290
Intent	3900	0.7179

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

Stage	Customers	Stage conversion to next
Evaluation	2800	0.5714
Purchase	1600	0.7500
Consumption	1200	0.5833
Advocacy	700	—

IV. METHODS FOR CUSTOMER JOURNEY MAPPING AND OPTIMIZATION

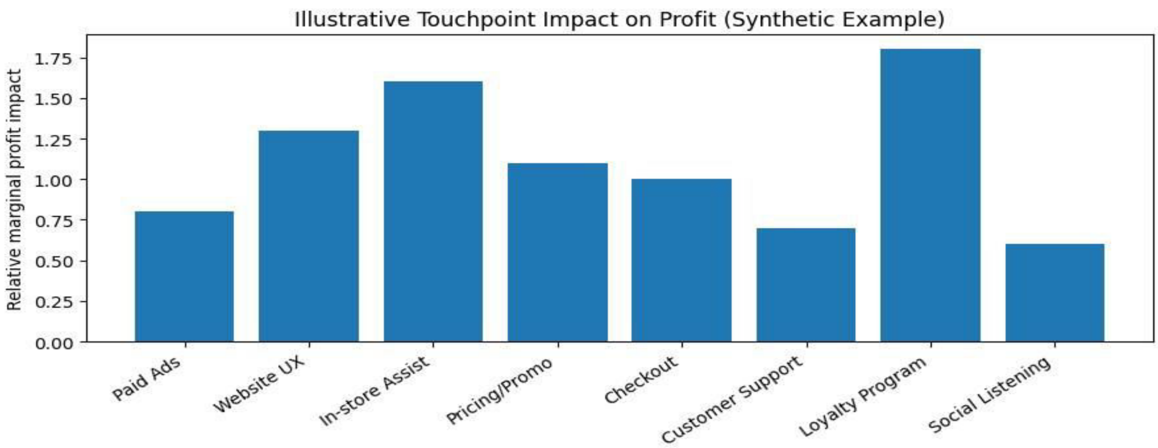
Customer journey mapping, a principle in service design research, visualizes steps taken by customers to fulfill a goal, such as buying a product. In a marketing context, customer journeys integrate sub-processes such as information search, online or offline purchase, usage experience, and word-of-mouth communication within a coherent framework. Mapping the customer journey enables strategists to view customer highlights and pain points across touchpoints, facilitating experience improvement.

In the customer journey of a retail business, the aforementioned purchase and consumption processes are typically irrelevant for external customers. The customer journey for a retail business can therefore be divided into five stages: (1) pre-visit information search; (2) offline store visit (driven by individual information need, related to seasonal purchases or scheduled purchase of high-involvement products); (3) purchase in store, promoted by the omni-channel system (linked to real-time inventory information or price discrepancy between online and retail); (4) usage of goods or services, related to online and offline reviews or recommendations within social networks; and (5) post-visit word-of-mouth communication. All stages feature various customer touchpoints for interaction and information exchange with the business. The purpose is to collect and analyze information from real-time user data to facilitate customer journey optimization and enhance overall business performance in the retail industry.

4.1. Customer Journey Mapping

Customer journey mapping in smart retail begins with the understanding that the retail journey of a customer involves six phases: need awareness, information gathering, consideration, purchase, use, and post-use evaluation. These phases can be further broken down into several touchpoints. The customer journey map resembles a customer experience pyramid with three primary bases at the bottom—the customer segment, brand evaluation for reference, and product area. Identified segments participate in a more in-depth journey map. A comprehensive journey map includes touchpoints, stages, key actions, metrics, pain points, and opportunities.

Bang and Wang (2021) emphasize that optimizing the journey, clarifying the business-related smart retail trajectory segments, and quantifying these stages according to changes in sales metrics require a plethora of customer journey metrics. For example, interest levels at the funnel's top influence audience size at the bottom, while bounce and repeat rates provide insight into advertising channel effectiveness. However, sharing audience-quality, real-time-state information across channels can reduce marketing costs and enhance return-on-investment. Journey modeling also helps identify business-themed troubleshooting topics that impact conversion rates. The task then shifts from journey mapping to optimization and is often modeled as a prediction problem, requiring different metrics for the target line and above-or-below points.



| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

Equation 2) Experience metrics

2.1 Net Promoter Score (NPS)

Survey question (0–10): "How likely to recommend?"

- Promoters: scores 9–10 → count P
- Passives: 7–8 → count A
- Detractors: 0–6 → count D
- Total $T = P + A + D$

Step-by-step:

2. Promoter share:

$$p = \frac{P}{T}$$

3. Detractor share:

$$d = \frac{D}{T}$$

4. NPS definition:

$$\text{NPS} = (p - d) \times 100$$

4. Substitute:

$$\boxed{\text{NPS} = \left(\frac{P}{T} - \frac{D}{T}\right) \times 100}$$

2.2 Customer Satisfaction Score (CSAT) – Top-2 box version

Assume a 1–5 scale; "satisfied" often means 4 or 5.

Let r_i be rating of customer i, $i = 1..n$.

Step-by-step:

3. Indicator of satisfaction:

$$\mathbb{1}(r_i \geq 4) = \begin{cases} 1, & r_i \in \{4,5\} \\ 0, & \text{otherwise} \end{cases}$$

4. Fraction satisfied:

$$\frac{1}{n}\sum_{i=1}^{n} \mathbb{1}\,(r_i \geq 4)$$

3. Convert to percentage:

$$\boxed{\text{CSAT}_{\text{Top2}} = \left(\frac{1}{n}\sum_{i=1}^{n} \mathbb{1}\,(r_i \geq 4)\right) \times 100}$$

4.2. Predictive Analytics and Personalization

Prediction entails anticipating future behavior predicated upon both historic data patterns and contemporary circumstances, whether for solely decision-making, for intelligence of an intelligent actor, or to facilitate interaction with an adaptive system. Predictive models capable of correlating relevant analysis factors with anticipated behavior can therefore furnish AI agents with suggestions for when the appropriate action is likely to be highly beneficial or, for sponsors of social agents, to delineate the antecedent conditions under which the target actions might be of particular interest.

Personalization involves interfacing adaptation to individual consumers or groups in a manner that extends beyond basing the state of all stimuli upon their collective average behavior up to any specific time; rather, the aim is to foster especially profitable, or at least favorable, connections with specific individuals or groups of individuals. Thus, personalizing an interaction path entails dynamically predicting the behavior of specific individuals or markets and adjusting individual or targeted touchpoints toward optimizing the entire interaction across multiple participants. Because genuinely personal experiences depend upon current context, prediction is critical for making personalization effective and valuable on all scales.

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

V. AI TECHNIQUES FOR BIG DATA IN RETAIL

Machine Learning (ML) and Deep Learning (DL) are closely related areas of research with numerous applications in retailing. Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are also applicable in retail analytics. Investigations addressed Customer Satisfaction Prediction, Customer Loyalty Prediction, Customer Relationship Management, Customer Churn Prediction, Customer attrition Prevention, Demand Forecasting, Product Demand Prediction and Facial Recognition. Data mining algorithms have been compared for Customer Lifetime Value prediction, product demand forecasting and expert decision-making. These algorithms have also been used for identifying key areas of online shopping sites and evaluating service quality. Support Vector Machines (SVM) have been proposed for predicting the end point of the customer journey and Semantic Network-based Classification Methods (SNCM) for improving online purchase intention prediction.

Natural Language Processing (NLP), an interdisciplinary field of linguistics and artificial intelligence, enables the recognition and understanding of human languages and is therefore particularly important for improving Customer Experience. Sentiment analysis, which involves text classification into categories such as positive, negative or neutral, also requires NLP methods. Sentiment analysis of social media content provides insights into brand perception, while movie reviews reveal user opinions and feelings. Apart from these applications, NLP techniques are utilized for tracking user reaction to marketing campaigns, understanding marketing messages, and classifying product reviews expressed in natural languages. Other NLP applications include Customer Voice Mining, Customer Insights Identification, Customer Feedback Analysis and Conversational Agents. Some modelling proposals require unstructured text inputs, making pre-labelling unfeasible, while Poor Data Quality, data Labelling Efforts, Overfitting and Processing Time must also be considered.

Equation 3) Touchpoint optimization on profit → math model

A practical mathematical form is:

3.1 Profit as baseline + touchpoint lift

Let:

- Touchpoints indexed by $t = 1..T$
- Decision variable x_t = investment level / intensity (budget, impressions, staffing hours, etc.)
- a_t = marginal profit contribution per unit of x_t
- c_t = cost per unit of x_t
- B = budget
- Π_0 = baseline profit without extra intervention

Step-by-step:

4. Net profit contribution per touchpoint:

$$(a_t - c_t)x_t$$

5. Total profit:

$$\Pi = \Pi_0 + \sum_{t=1}^{T} (a_t - c_t)\, x_t$$

4. Budget constraint:

$$\sum_{t=1}^{T} c_t\, x_t \le B$$

5. Nonnegativity (and optional upper bounds $x_t \le u_t$):

$$x_t \ge 0$$

5. Optimization statement:

$$\boxed{\max_{x_1..x_T} \Pi_0 + \sum_{t=1}^{T} (a_t - c_t)\, x_t \quad \text{s.t.} \quad \sum_{t=1}^{T} c_t\, x_t \le B,\ x_t \ge 0}$$

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

3.2 If you want "journey-aware" optimization (stage conversions)

Let stage conversion at step s be a function of touchpoints affecting that stage:

$$\mathrm{CR}_{s\to s+1}(x) = \sigma\left(\beta_{s0} + \sum_{t\in\mathcal{T}(s)} \beta_{st}\, x_t\right)$$

where $\sigma(z) = \frac{1}{1+e^{-z}}$ is logistic.

Then purchases:

$$N_{\mathrm{Pur}}(x) = N_{\mathrm{Awr}} \cdot \prod_{s=\mathrm{Awr}}^{\mathrm{Eval}} \mathrm{CR}_{s\to s+1}(x)$$

and profit could be:

$$\Pi(x) = \mathrm{margin} \cdot N_{\mathrm{Pur}}(x) - \sum_t c_t\, x_t$$

5.1. Machine Learning and Deep Learning Applications

Various machine learning and deep learning methods are tailored to different aspects of retail analytics. Specific models excel in predicting whether a purchase will occur, others provide recommended offers, and still others contribute to providing an overall score for the satisfaction of the customers. Predictive analytics requires methods that can accommodate the unique characteristics of the data being analyzed, including quality, quantity, availability, type, and nature. For decision-related problems, research findings support the need for neural networks rather than decision trees. Accuracy is generally not the primary consideration; rather, it is important for the chosen supervised learning method to provide valuable output for the decision process. Customer and sales forecasts and market-basket analysis require the support of specific methods such as time series and association rule techniques, respectively, that are outside the realm of predictive analytics.

Despite these specialities, it is believed that the different areas of retail analytics might benefit from a common approach. The data available for customer journey analytics is often vast, noisy, and represents reality only approximately. Consequently, a large volume of discarded relevant information is likely. Therefore, using different types of learning methods in ensembling techniques is of great value (and is widely applicable). Such ensembling directs the mining process towards a broad overview. Retailers can collect customers' whole journeys autonomously, thus allowing for large-sample analyses, as well as testing for new factors deemed important. Different models provide complementary aspects and, combined, explain the package of decisions in a full celebrity-cadre-behaviour way. Resampling techniques and neural networks that automatically model the underlying relations, allow for more continuous media-campaign allocation and for a more robust approach in terms of prediction certainty.

5.2. Natural Language Processing for Customer Insights

Various tools, technologies, and techniques focus on understanding customer needs, preferences, opinions, and experiences through unstructured text sources. For instance, online reviews about retailers, their brands, competitors, and the industry in general can deliver valuable insights when investigated properly. Therefore, the first step in an NLP analysis is the identification of the data source(s), which can include Web scraped reviews, social media posts (e.g., Twitter, Reddit, or Facebook), survey text (e.g., open-ended questions) or feedback comments (e.g., quality evaluation of a product or service), audio transcripts of customer service calls, and textual comparisons of products from online retailers. When conducting sentiment analysis in social media, the existence of a larger corpus helps to avoid particularities related to the segments, products, and services (e.g., emojis or memes), and the sentiment classification can rely on deep learning. The analysis of a customer's complete journey, from attraction to retention/loyalty, can use the analysis of the reviews of more focused but more detailed locations, such as mid and last steps.

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

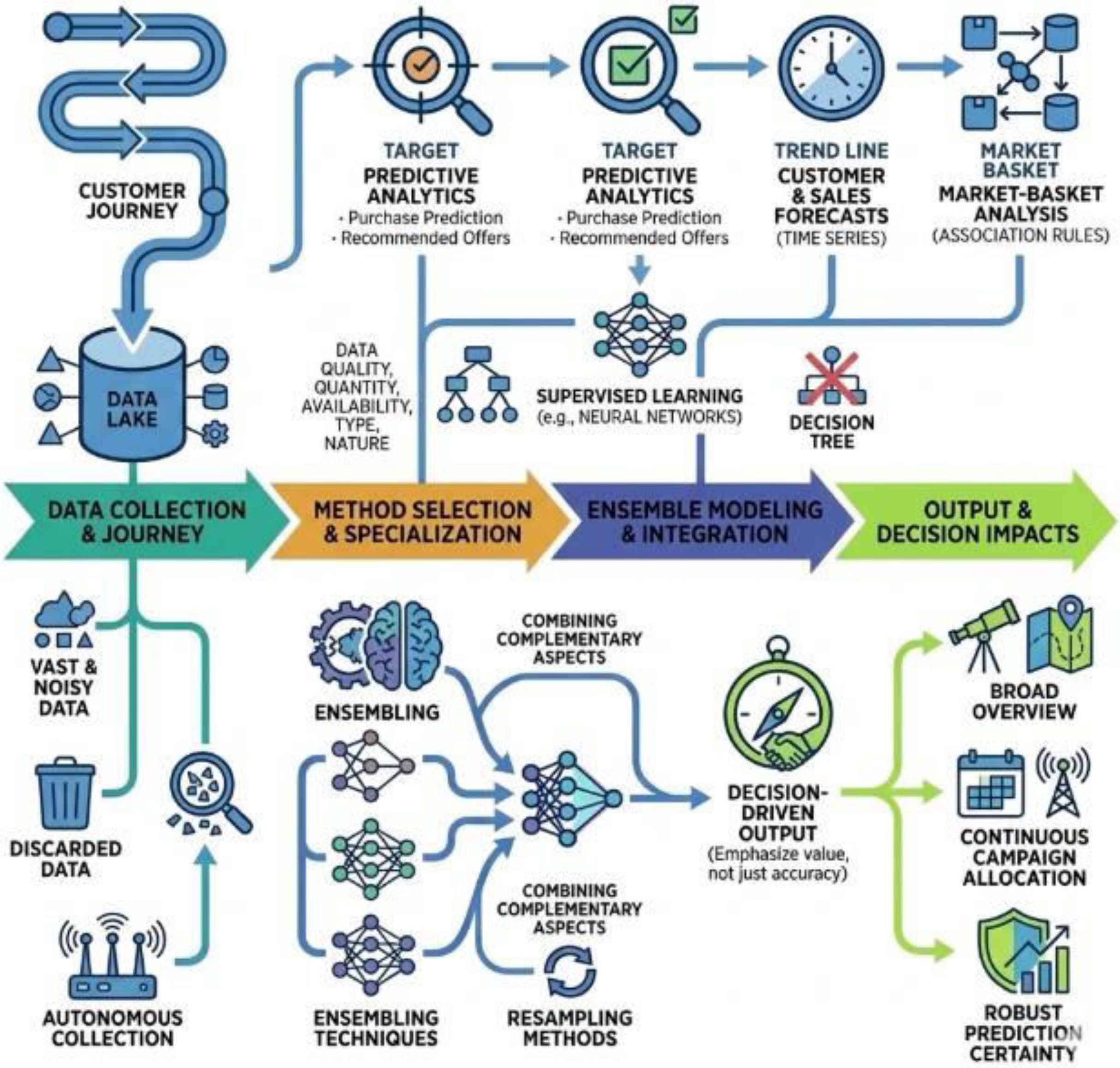


Fig 3: From Specialized Models to Integrated Ensembles: A Robust Framework for Decision-Centric Retail Analytics

The type of analysis shapes the textual corpus generation. Topic modeling methods (e.g., Latent Dirichlet Allocation or Non-Negative Matrix Factorization) generally need larger data distributions, while analysis focusing on particular brands, products, retailers, locations, or services are more suitable for word frequency or word-cloud analysis. Identifying important terms may also help direct more specific analyses on those topics by using sentiment analysis or sentiment classification. Sentiment classification, in turn, can shed more light on a particular subject (a product, brand, store, or company) or aspect (service, price, quality, and others) by providing the sentiment associated with it, and enables comparison based on different groups, and even comparison with the industry or competition in sentiment analysis on Twitter. Such techniques may also take advantage of transfer learning by using pre-trained models on customer experiences (e.g., Customer Review Sentiment Analysis across Domains). Given that most models are trained in English due to the quantity of available data (e.g., in the Amazon repository), techniques like translation or dictionaries extend sentiment classification to other languages.

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

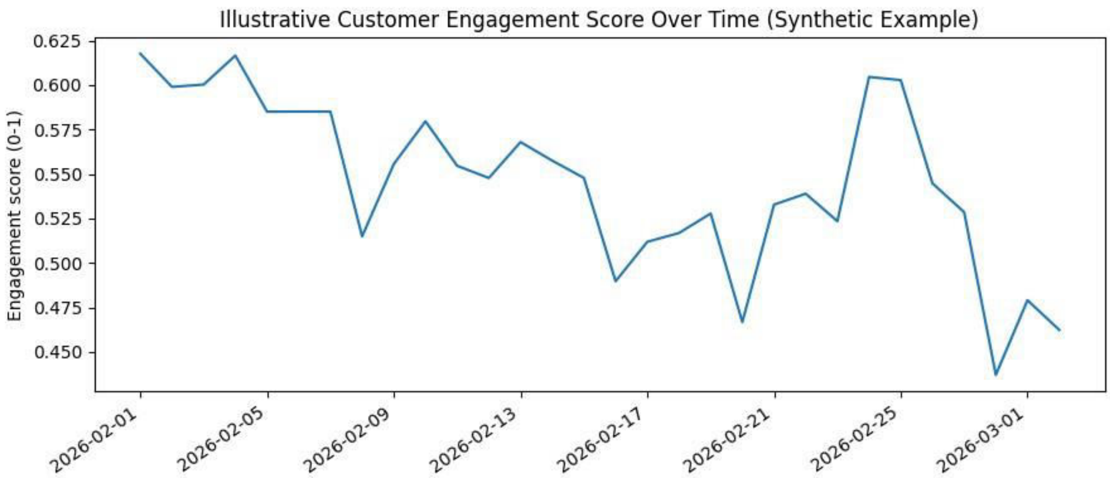
|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

VI. DATA GOVERNANCE, ETHICS, AND PRIVACY IN RETAIL ANALYTICS

A thorough data governance framework is a prerequisite for successful Smart Retail initiatives. Responsibility for data ownership, custodianship, and stewardship must be clearly defined and communicated among stakeholders and management levels. Trade-offs between data governance and democratization must be carefully assessed when enabling broader access to analytics-driven insights. Ethical frameworks can provide guidance when assessing sensitive decisions that directly affect customers and broader society. Transparency around algorithmic procedures and choices, especially related to customer feedback and sentiment analysis, is a requirement for managing reputation risks. Transparency and oversight are increasingly being demanded for ML algorithmic decision-making, along with a readiness to provide explanations for actions taken by agents, such as chatbots or virtual agents. Privacy by design principles must be embedded within all development work focused on data, its usage, analytics and algorithm creation are often governed by local regulation but also possess common requirements for customer trust and mitigation of reputation damages.

The analytical processes executed against the data can yield higher-level considerations requiring higher levels of privacy governance. Models for analytics and rapid customer feedback that require more significant processing of data are susceptible to damage from potential PI leaks. Compliance with regulatory requirements assists in generating public trust, and good practice in these analytics remains a high concern and priority. Overall data governance and assurance frameworks that allow for distributed data ecosystems require additional scrutiny and good governance practices for further privacy assurance.



Equation 4) Predictive analytics equation
A standard purchase-probability model:
Logistic regression (purchase vs not)
Let $y_i \in \{0,1\}$ indicate purchase for customer i, and x_i be features.
Step-by-step:
5. Linear score:

$$z_i = \beta_0 + \beta^\top x_i$$

6. Convert score to probability via logistic:

$$p_i = P(y_i = 1|x_i) = \frac{1}{1 + e^{-z_i}}$$

5. Final:

$$\boxed{P(y_i = 1|x_i) = \frac{1}{1 + \exp\left(-(\beta_0 + \beta^\top x_i)\right)}}$$

6.1. Navigating Data Governance, Ethical Considerations, and Privacy Challenges in Retail Analytics
Data governance—comprising principles, policies, and procedures for data management—facilitates the effective use of data, aligning it with organizational strategies. Key elements include data quality, integrity, security, and legal

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

compliance. Implementing a governance structure for big data presents additional challenges associated with massive volumes, varied formats, and multiple stakeholders; hence, a hybrid approach—combining a centralized framework with decentralized implementation—proves most effective. In AI-powered analytics, effective data governance establishes processes for managing data assets, enforcing privacy regulations, and building customer trust.

Governance of data utilized for AI-powered analytics should encompass regulations for stimulating its ethical use in society. Indeed, studies report that the lack of ethical and legal considerations is detrimental to such analytics. Furthermore, public concerns for data ethics and privacy of all parties (retailers, suppliers, consumers) involved in an AI-powered customer journey must guide the overall analytics process. Retailers also need to ensure transparency and robustness of the employed AI algorithms. Moreover, guidelines should be established to avoid inappropriate and malicious uses of the analytics. Finally, a solid data-risk-management strategy is key for trustworthy customer interaction.

Governance of data utilized for AI-powered analytics should encompass regulations for stimulating its ethical use in society. Indeed, studies report that the lack of ethical and legal considerations is detrimental to such analytics. Furthermore, public concerns for data ethics and privacy of all parties (retailers, suppliers, consumers) involved in an AI-powered customer journey must guide the overall analytics process. Retailers also need to ensure transparency and robustness of the employed AI algorithms. Moreover, guidelines should be established to avoid inappropriate and malicious uses of the analytics. Finally, a solid data-risk-management strategy is key for trustworthy customer interaction.

VII. CONCLUSION

AI's predictive capabilities are the most promising lever to achieve a deep understanding of customer behavior and preferences and consequently offer a personalized customer experience within the retail ecosystem. However, the technological implementation of AI-powered predictive analytics represents only one of the primary elements of a successful strategy.

The research outlined the factors that every retailer, platform, and marketplace must take care of to achieve a solid retail intelligence Data Ecosystem Data Engineering for modeling the Customer Journey Mapping Optimization and Data Chanels Management design an architecture able to collect and integrate data from every possible data source across the organization, including processes, customers, products, operations, marketing & sales, and finance. Use the acquired data to build and optimize the entire Customer Experience Journey from awareness to retention. Leverage the channel data to enhance intelligence on how to bash & enjoy revenues.

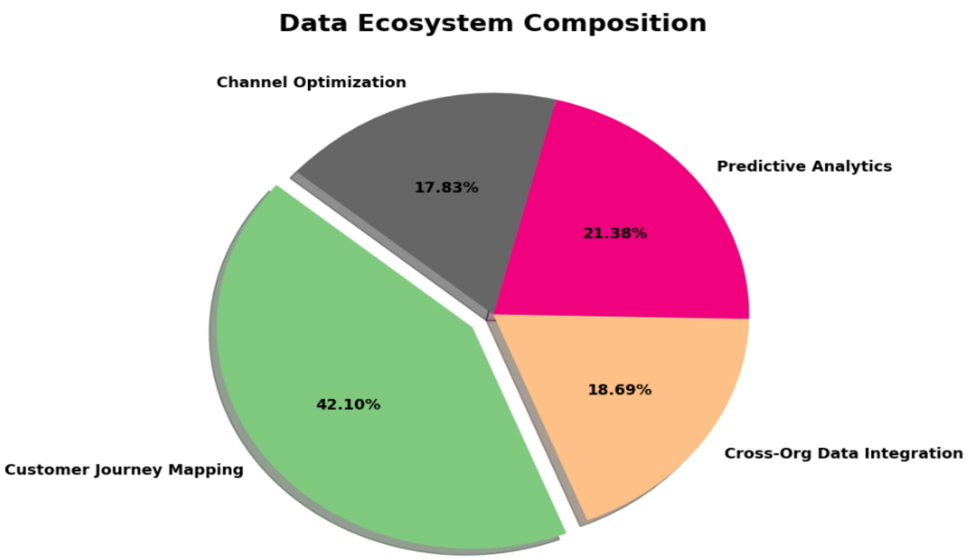


Fig 4: Data Ecosystem Composition

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

7.1. Summary and Future Directions in AI-Driven Retail Analytics

AI-driven analytics leverage data acquisition and integration from multiple sources within and beyond organizational boundaries, resulting in data ecosystems that provide a holistic perspective for enhanced intelligence by overcoming the traditional silos of proprietary business data of market players. Customer journey mapping and optimization have emerged as high-interest research areas, supported by the foundation of a theoretical framework, encompassing the customer journey concept and stages, touchpoints along the journey, and the metrics for mapping the journey. AI techniques appropriate for customer journey mapping and optimization have been examined.

Analysts and researchers are focusing on AI techniques based on machine learning and deep learning for AI-driven big data analytics, data-driven decision-making, and intelligent process automation in almost all aspects of business operations. In retail, a large and fast-growing sector, these techniques serve customer behavior prediction, sales forecasting, supply chain and inventory management, customer journey mapping, recommendation systems, and efficiency improvement in operations like warehouse and store management. The natural language processing (NLP) subfield of AI is particularly suitable for analyzing large volumes of unstructured textual data for insights into product, service, and brand sentiment among customers, and for automatically interpreting customer feedback on products and services. The dependent data for specific applications determine their importance and weight in overall customer journey mapping and optimization within the retail sector.

AI-driven analytics for smart retail organizations leverage data from heterogeneous sources, apply advanced algorithms for value extraction, and ensure that the results are suitably processed and integrated into the systems and processes that will make best use of them. Thus, the analysis incorporates analytics foundations, a representation for novel retail data ecosystems, customer journey mapping and optimization workflows for customer-facing analytics, and models for the synthesis of these elements into a coherent AI-driven data analytics capability that responds to the current needs of smart retail organizations.

REFERENCES

1. Meda, R. (2023). Data Engineering Architectures for Scalable AI in Paint Manufacturing Operations. European Data Science Journal (EDSJ) p-ISSN 3050-9572 en e-ISSN 3050-9580, 1(1).
2. Kalisetty, S., & Singireddy, J. (2023). Optimizing Tax Preparation and Filing Services: A Comparative Study of Traditional Methods and AI Augmented Tax Compliance Frameworks. Available at SSRN 5206185.
3. Kshetri, N. (2022). Cybersecurity in cloud computing: Emerging technologies and challenges. IT Professional, 24(3), 6–12.
4. Gottimukkala, V. R. R. (2022). Licensing Innovation in the Financial Messaging Ecosystem: Business Models and Global Compliance Impact. International Journal of Scientific Research and Modern Technology, 1(12), 177-186.
5. Kolla, S. H. (2021). Rule-Based Automation for IT Service Management Workflows. Online Journal of Engineering Sciences, 1(1), 1–14. Retrieved from https://www.scipublications.com/journal/index.php/ojes/article/view/1360
6. Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., et al. (2016). FAIR Guiding Principles. Scientific Data, 3, 160018.
7. Zhang, Y., & Yang, Q. (2021). A survey on multi-task learning. IEEE Transactions on Knowledge and Data Engineering, 34(12), 5586–5609.
8. Meda, R. (2023). Developing AI-Powered Virtual Color Consultation Tools for Retail and Professional Customers. Journal for ReAttach Therapy and Developmental Diversities. https://doi. org/10.53555/jrtdd. v6i10s (2), 3577.
9. Almadhoun, R., Kadadha, M., Al-Fuqaha, A., & Guizani, M. (2021). A user-centric blockchain-based system for incident response in the era of IoT. Internet of Things, 14, 100371. https://doi.org/10.1016/j.iot.2021.100371
10. Kalisetty, S. (2023). The Role of Circular Supply Chains in Achieving Sustainability Goals: A 2023 Perspective on Recycling, Reuse, and Resource Optimization. Reuse, and Resource Optimization (June 15, 2023).
11. Little, R. J. A., & Rubin, D. B. (2002). Statistical analysis with missing data. Wiley.
12. Siva Hemanth Kolla. (2022). Knowledge Retrieval Systems for Enterprise Service Environments. International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 495–506. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/8037
13. Bishop, C. M. (1994). Novelty detection and neural network validation. IEE Proceedings, 141(4), 217–222.
44. Singireddy, J. (2023). Finance 4.0: Predictive analytics for financial risk management using AI. European Journal of Analytics and Artificial Intelligence (EJAAI) p-ISSN, 3050-9556.
15. Cook, D. J., & Holder, L. B. (2006). Mining graph data. Wiley.

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

16. Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2015). Time series analysis: Forecasting and control. Wiley.
17. Amistapuram, K. (2022). Fraud Detection and Risk Modeling in Insurance: Early Adoption of Machine Learning in Claims Processing. Available at SSRN 5741982.
18. Kumar, A., Gupta, P., & Singh, R. (2023). Sentiment analysis methods for proactive brand reputation risk management. International Journal of Information Management Data Insights, 3(1).
19. Ramesh Inala. (2023). Big Data Architectures for Modernizing Customer Master Systems in Group Insurance and Retirement Planning. Educational Administration: Theory and Practice, 29(4), 5493–5505. https://doi.org/10.53555/kuey.v29i4.10424
20. Aggarwal, C. C. (2017). Outlier analysis (2nd ed.). Springer.
21. Davuluri, P. N. AI-Augmented Sanctions Screening: Enhancing Accuracy and Latency in Real Time Compliance Systems.
22. Bifet, A., & Gavalda, R. (2007). Learning from time-changing data with adaptive windowing. SDM Proceedings.
23. Ruff, L., Vandermeulen, R. A., Görnitz, N., et al. (2018). Deep one-class classification. ICML Proceedings.
24. Annapareddy, V. N., Preethish Nandan, B., Kommaragiri, V. B., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing.
25. Salfner, F., Lenk, M., & Malek, M. (2010). Survey of failure prediction methods. ACM Computing Surveys, 42(3), 1–42.
26. Nagubandi, A. R. (2023). Advanced Multi-Agent AI Systems for Autonomous Reconciliation Across Enterprise Multi-Counterparty Derivatives, Collateral, and Accounting Platforms. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 653-674.
27. Schölkopf, B., Platt, J. C., Shawe-Taylor, J., et al. (2001). Estimating the support of a high-dimensional distribution. Neural Computation, 13(7), 1443–1471.
28. Kalisetty, S., & Ganti, V. K. A. T. (2019). Transforming the Retail Landscape: Srinivas's Vision for Integrating Advanced Technologies in Supply Chain Efficiency and Customer Experience. Online Journal of Materials Science, 1, 1254.
29. Sipos, R., Fradkin, D., Moerchen, F., & Wang, Z. (2014). Log-based predictive maintenance. KDD Proceedings.
30. Meda, R. (2023). Intelligent Infrastructure for Real-Time Inventory and Logistics in Retail Supply Chains. Educational Administration: Theory and Practice.
31. Kolla, S. K. (2021). Designing Scalable Healthcare Data Pipelines for Multi-Hospital Networks. World Journal of Clinical Medicine Research, 1(1), 1–14. Retrieved from https://www.scipublications.com/journal/index.php/wjcmr/article/view/1376
32. Bandi, V. D. V. K. (2023). Cloud-Native Model Lifecycle Management for Enterprise AI Systems. International Journal of Scientific Research and Modern Technology, 2(12), 78–90. https://doi.org/10.38124/ijsrmt.v2i12.1236
33. Inala, R. Revolutionizing Customer Master Data in Insurance Technology Platforms: An AI and MDM Architecture Perspective.
34. Tibshirani, R. (1996). Regression shrinkage and selection via the Lasso. Journal of the Royal Statistical Society B, 58(1), 267–288.
35. Gottimukkala, V. R. R. (2023). Privacy-Preserving Machine Learning Models for Transaction Monitoring in Global Banking Networks. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 633-652.
36. Tukey, J. W. (1977). Exploratory data analysis. Addison-Wesley.
37. AI Powered Fraud Detection Systems: Enhancing Risk Assessment in the Insurance Sector. (2023). American Journal of Analytics and Artificial Intelligence (ajaai) With ISSN 3067-283X, 1(1). https://ajaai.com/index.php/ajaai/article/view/14
38. Weber, G. M., Mandl, K. D., & Kohane, I. S. (2014). Finding the missing link for big biomedical data. JAMIA, 21(1), 1–3.
39. Maguluri, K. K., Pandugula, C., Kalisetty, S., & Mallesham, G. (2022). Advancing Pain Medicine with AI and Neural Networks: Predictive Analytics and Personalized Treatment Plans for Chronic and Acute Pain Managements. Journal of Artificial Intelligence and Big Data, 2(1), 112-126.
40. Garapati, R. S. (2022). AI-Augmented Virtual Health Assistant: A Web-Based Solution for Personalized Medication Management and Patient Engagement. Available at SSRN 5639650.
41. Goldstein, M., & Uchida, S. (2016). A comparative evaluation of unsupervised anomaly detection algorithms. Pattern Recognition, 64, 206–223.
42. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

43. Segireddy, A. R. (2021). Containerization and Microservices in Payment Systems: A Study of Kubernetes and Docker in Financial Applications. Universal Journal of Business and Management, 1(1), 1–17. Retrieved from https://www.scipublications.com/journal/index.php/ujbm/article/view/1352
44. He, J., Baxter, S. L., Xu, J., et al. (2019). The practical implementation of AI in healthcare. Nature Medicine, 25(1), 30–36.
45. Inala, R. AI-Powered Investment Decision Support Systems: Building Smart Data Products with Embedded Governance Controls.
46. Hripcsak, G., & Albers, D. J. (2013). Next-generation phenotyping. JAMIA, 20(1), 117–121.
47. Gottimukkala, V. R. R. (2021). Digital Signal Processing Challenges in Financial Messaging Systems: Case Studies in High-Volume SWIFT Flows.
48. Iglewicz, B., & Hoaglin, D. C. (1993). How to detect and handle outliers. ASQC.
49. Johnson, A. E. W., Pollard, T. J., Shen, L., et al. (2016). MIMIC-III database. Scientific Data, 3, 160035.
50. Yandamuri, U. S. (2022). Big Data Pipelines for Cross-Domain Decision Support: A Cloud-Centric Approach. International Journal of Scientific Research and Modern Technology, 1(12), 227–237. https://doi.org/10.38124/ijsrmt.v1i12.1111
51. Kimball, R., & Caserta, J. (2004). The data warehouse ETL toolkit. Wiley.
52. Davuluri, P. N. Integrating Artificial Intelligence into Event-Driven Financial Crime Compliance Platforms.
53. Kriegel, H. P., Kröger, P., Schubert, E., & Zimek, A. (2009). Outlier detection in axis-parallel subspaces. PKDD Proceedings, 831–838.
54. Kummari, D. N. (2023). AI-Powered Demand Forecasting for Automotive Components: A Multi-SupplierV Data Fusion Approach. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 1(1).
55. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.
56. Nagabhyru, K. C. (2023). From Data Silos to Knowledge Graphs: Architecting CrossEnterprise AI Solutions for Scalability and Trust. Available at SSRN 5697663.
57. Zaharia, M., Chowdhury, M., Franklin, M. J., et al. (2010). Spark: Cluster computing. HotCloud Proceedings.
58. Avinash Reddy Aitha. (2022). Deep Neural Networks for Property Risk Prediction Leveraging Aerial and Satellite Imaging. International Journal of Communication Networks and Information Security (IJCNIS), 14(3), 1308–1318. Retrieved from https://www.ijcnis.org/index.php/ijcnis/article/view/8609
59. Goutham Kumar Sheelam, Hara Krishna Reddy Koppolu. (2022). Data Engineering And Analytics For 5G-Driven Customer Experience In Telecom, Media, And Healthcare. Migration Letters, 19(S2), 1920–1944. Retrieved from https://migrationletters.com/index.php/ml/article/view/11938
60. Alenezi, M., & Akour, M. AI-driven innovations in software engineering: A review of current practices and future directions. Applied Sciences, 15(3), 1344. https://doi.org/10.3390/app15031344 Cited by: 149
61. Kummari, D. N. (2023). Energy Consumption Optimization in Smart Factories Using AI-Based Analytics: Evidence from Automotive Plants. Journal for Reattach Therapy and Development Diversities. https://doi. org/10.53555/jrtdd. v6i10s (2), 3572.
62. Bates, D. W., Saria, S., Ohno-Machado, L., et al. (2014). Big data in health care. Health Affairs, 33(7), 1123–1131.
63. Keerthi Amistapuram. (2023). Privacy-Preserving Machine Learning Models for Sensitive Customer Data in Insurance Systems. Educational Administration: Theory and Practice, 29(4), 5950–5958. https://doi.org/10.53555/kuey.v29i4.10965
64. Belle, A., Thiagarajan, R., Soroushmehr, S. M. R., et al. (2015). Big data analytics in healthcare. BioMed Research International, 2015, 370194.
65. Guntupalli, R. (2023). AI-Driven Threat Detection and Mitigation in Cloud Infrastructure: Enhancing Security through Machine Learning and Anomaly Detection. Available at SSRN 5329158.
66. Breunig, M. M., Kriegel, H. P., Ng, R. T., & Sander, J. (2000). LOF: Identifying density-based local outliers. ACM SIGMOD Record, 29(2), 93–104.
67. Unifying Data Engineering and Machine Learning Pipelines: An Enterprise Roadmap to Automated Model Deployment. (2023). American Online Journal of Science and Engineering (AOJSE) (ISSN: 3067-1140) , 1(1). https://aojse.com/index.php/aojse/article/view/19
68. Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. Mobile Networks and Applications, 19(2), 171–209.
69. Singireddy, S. (2023). AI-Driven Fraud Detection in Homeowners and Renters Insurance Claims. Journal for Reattach Therapy and Development Diversities. https://doi. org/10.53555/jrtdd. v6i10s (2), 3569.
70. Cios, K. J., & Moore, G. W. (2002). Uniqueness of medical data mining. Artificial Intelligence in Medicine, 26(1–2), 1–24.

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

71. Kummari, D. N., & Burugulla, J. K. R. (2023). Decision Support Systems for Government Auditing: The Role of AI in Ensuring Transparency and Compliance. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 493-532.
72. Braik, A., & Koliou, M. Artificial intelligence and machine learning-powered GIS for proactive disaster resilience in a changing climate. Journal of Spatial Science, 69(1).
73. Challa, K. (2023). Dynamic Neural Network Architectures for Real-Time Fraud Detection in Digital Payment Systems Using Machine Learning and Generative AI. Nanotechnology Perceptions.
74. Dwork, C. (2008). Differential privacy. ICALP Proceedings, 1–12.
75. Bandi, V. D. V. K. (2023). Production-Grade Machine Learning Pipelines For Healthcare Predictive Analytics. South Eastern European Journal of Public Health, 189–205. Retrieved from https://www.seejph.com/index.php/seejph/article/view/7057
76. Kolla, S. K. (2021). Architectural Frameworks for Large-Scale Electronic Health Record Data Platforms. Current Research in Public Health, 1(1), 1–19. Retrieved from https://www.scipublications.com/journal/index.php/crph/article/view/1372
77. Arundel, J., Li, S. T., & Wang, J. (2020). Geographic information systems and artificial intelligence for disaster management. International Journal of Geographical Information Science, 34(10). https://doi.org/10.1080/13658816.2020.1755041
78. Venkata Bhardwaj and Gadi, Anil Lokesh and Kalisetty, Srinivas, Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing (December 15, 2022).
79. Ahmed, M., Mahmood, A. N., & Hu, J. (2016). A survey of network anomaly detection techniques. Journal of Network and Computer Applications, 60, 19–31.
80. Uday Surendra Yandamuri. (2023). An Intelligent Analytics Framework Combining Big Data and Machine Learning for Business Forecasting. International Journal Of Finance, 36(6), 682-706. https://doi.org/10.5281/zenodo.18095256
81. Aljawarneh, S., Aldwairi, M., & Yassein, M. B. (2018). Anomaly-based intrusion detection system through feature selection analysis and building hybrid efficient model. Journal of Computational Science, 25, 152–160.
82. Li, Y., Chen, C. Y., Wasserman, W. W., & Ramani, A. K. (2016). Deep feature selection. Bioinformatics, 32(5), 743–750.
83. Kalisetty, S., & Singireddy, J. (2023). Agentic AI in retail: A paradigm shift in autonomous customer interaction and supply chain automation. American Advanced Journal for Emerging Disciplinaries (AAJED) ISSN, 3067-4190.
84. Malhotra, P., Vig, L., Shroff, G., & Agarwal, P. (2015). Long short-term memory networks for anomaly detection. ESANN Proceedings.
85. Kalisetty, S., Vankayalapati, R. K., Reddy, L., Sondinti, K., & Valiki, S. (2022). AI-Native Cloud Platforms: Redefining Scalability and Flexibility in Artificial Intelligence Workflows. Linguistic and Philosophical Investigations, 21(1), 1-15.
86. Garapati, R. S. (2023). Optimizing Energy Consumption in Smart Build-ings Through Web-Integrated AI and Cloud-Driven Control Systems.
87. Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). Deep learning for healthcare. Briefings in Bioinformatics, 19(6), 1236–1246.
88. Kushvanth Chowdary Nagabhyru. (2023). Accelerating Digital Transformation with AI Driven Data Engineering: Industry Case Studies from Cloud and IoT Domains. Educational Administration: Theory and Practice, 29(4), 5898–5910. https://doi.org/10.53555/kuey.v29i4.10932
89. Shone, N., Ngoc, T., Phai, V., & Shi, Q. (2022). Deep learning approach to network intrusion detection. IEEE Transactions on Emerging Topics in Computational Intelligence, 6(1), 88–99.
90. Guntupalli, R. (2023). Optimizing Cloud Infrastructure Performance Using AI: Intelligent Resource Allocation and Predictive Maintenance. Available at SSRN 5329154.
91. Patcha, A., & Park, J. M. (2007). An overview of anomaly detection techniques. Computer Networks, 51(12), 3448–3470.
92. Pedregosa, F., Varoquaux, G., Gramfort, A., et al. (2011). Scikit-learn. Journal of Machine Learning Research, 12, 2825–2830.
93. Aitha, A. R. (2023). CloudBased Microservices Architecture for Seamless Insurance Policy Administration. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 607-632.
94. Alshamrani, A., Myneni, S., Chowdhary, A., & Huang, D. (2023). A survey on advanced persistent threats: Techniques and detection methods. IEEE Communications Surveys & Tutorials, 25(1), 143–171.

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 6, Issue 6, November–December 2023||

DOI:10.15662/IJRAI.2023.0606030

95. Avinash Reddy Segireddy. (2022). Terraform and Ansible in Building Resilient Cloud-Native Payment Architectures. International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 444–455. Retrieved from https://www.ijisae.org/index.php/IJISAE/article/view/7905.

96. Sarker, I. H., Kayes, A., & Watters, P. (2022). Cybersecurity data science: An overview from machine learning perspective. Journal of Big Data, 9(1), 1–29.

97. Lakkarasu, P., Kaulwar, P. K., Dodda, A., Singireddy, S., & Burugulla, J. K. R. (2023). Innovative computational frameworks for secure financial ecosystems: Integrating intelligent automation, risk analytics, and digital infrastructure. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 334-371.

98. Sarker, I. H. (2023). Machine learning-based cybersecurity: Methods, applications, and future research directions. Journal of Big Data, 10(1), 1–35.

99. Nandan, B. P., & Chitta, S. S. (2023). Machine Learning Driven Metrology and Defect Detection in Extreme Ultraviolet (EUV) Lithography: A Paradigm Shift in Semiconductor Manufacturing. Educational Administration: Theory and Practice, 29 (4), 4555–4568.

100. Ferrag, M. A., Shu, L., Yang, X., Derhab, A., & Maglaras, L. (2022). Security and privacy for green IoT-based agriculture: Review, blockchain solutions, and challenges. IEEE Access, 10, 1–20.

101. Pandiri, L., & Singireddy, S. (2023). AI and ML Applications in Dynamic Pricing for Auto and Property Insurance Markets. Journal for ReAttach Therapy and Developmental Diversities, 6, 2206-2223.

102. Aldhaheri, S., Alghazzawi, D., Cheng, L., Alzahrani, B., & Al-Barakati, A. (2023). Deep learning approaches for intrusion detection in cloud computing: A review. IEEE Access, 11, 11105–11124.

103. Challa, K. (2023). Transforming Travel Benefits through Generative AI: A Machine Learning Perspective on Enhancing Personalized Consumer Experiences. Educational Administration: Theory and Practice. Green Publication. Educational Administration: Theory and Practice. Green Publication. https://doi. org/10.53555/kuey. v29i4, 9241.

104. Ahmed, M., Mahmood, A. N., & Hu, J. (2022). A survey of network anomaly detection techniques. Journal of Network and Computer Applications, 60, 19–31.

105. Garapati, R. S. (2022). Web-Centric Cloud Framework for Real-Time Monitoring and Risk Prediction in Clinical Trials Using Machine Learning. Current Research in Public Health, 2, 1346.

106. Sarker, I. H., Kayes, A. S. M., Badsha, S., Watters, P., Ng, A., & Hammoudeh, M. (2022). Cybersecurity data science: An overview from machine learning perspective. Journal of Big Data, 9(1), 1–29.

107. Singireddy, S. (2023). Integrating Deep Learning and Machine Learning Algorithms in Insurance Claims Processing: A Study on Enhancing Accuracy, Speed, and Fraud Detection for Policyholders. Educational Administration: Theory and Practice, 29 (4), 4764–4776.

108. Kumar, R., Tripathi, R., & Agrawal, S. (2023). Machine learning techniques for intrusion detection systems in cloud environments. Computers & Security, 123, 102924.

109. Siva Hemanth Kolla. (2023). Deep Learning–Driven Retrieval-Augmented Generation for Enterprise ITSM Automation: A Governance-Aligned Large Language Model Architecture. Journal of Computational Analysis and Applications (JoCAAA), 31(4), 2489–2502. Retrieved from https://www.eudoxuspress.com/index.php/pub/article/view/4774.