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Research paper

Five-Tier BI Architecture with Tuned Decision Trees For E-Commerce Prediction

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Abstract

In recent times, remarkable performance has been shown by Large Language Models (LLMs) in a range of Natural Language Processing (NLP) such as questioning, responding, document production, and translating languages. In today's competitive business landscape, understanding consumer behaviour in online buying is crucial for the success of e-commerce platforms. The work proposes a novel Five-Tier Service-Oriented BI Architecture (FSOBIA) that leverages Advanced Tuned Decision Tree (ATDT) techniques for predicting online buying behaviour. The proposed FSOBIA offers e-commerce platforms a scalable and adaptable solution for gaining insights into consumer preferences and making informed business decisions. The goal of FSOBIA's design and implementation is to meet the needs of evolving users and provide quicker service. Experimental evaluations on real-world datasets in FSOBIA achieved over 95% prediction accuracy, outperforming traditional models: Decision Trees (82%) and XGBoost (91%), while offering better scalability and computational efficiency.

Keywords*: Five-Tier Service-Service Oriented BI Architecture, QoS-Aware Service Discovery, Tuned Decision Tree, Large Language Model Toolchain, Retrieval Augmented Generation*

1. Introduction

Organizations now have an expanding range of challenges and quick changes driven by rising user expectations, unclear borders, and faster software development cycles. We need a strong decision-support architecture [1] to get useful information from the huge amounts of data that transactions generate. Agents, web services, and loosely coupled software components make this architecture possible so that service providers may render Software as a Service (SaaS) easily available to consumers on demand. Numerous quality criteria, such as dependability and cost, compensate users for services [2]. We delete relevant session data at the end of obligations, thereby preserving only the final results. Advancing distributed applications across several sectors, including e-commerce, inventory management, sensor networks, and business intelligence (BI), depends on service-oriented computing. For in-depth research, business intelligence depends on a broad range of heterogeneous data sources [3]. Data sourcing, integration, cleaning, filtration, knowledge extraction, and insight building are a few of the various elements of the BI system.

Developing frameworks for decision support inside a service-oriented business intelligence environment is under much emphasis [4]. These systems use a multi-tiered approach to provide complete business analytics capability via communications between services. This approach creates an integrated data repository to operate as a mediator between corporate intelligence tools and local data sources. The data repositories are usually updated using push or pull strategies [5] because they don't have real-time data capabilities, which means that drill-down operations are limited to the design of the integrated data store. For innovative companies, developing effective methods to use high-dimensional data for significant outcomes is a major difficulty.

Recent developments in machine learning (ML) have enabled companies exactly project a spectrum of events. The combination of modern data modification technologies [6] with data mining approaches produces actionable knowledge. Both supervised and unsupervised learning approaches find value in forecasts. Data mining finds hidden patterns and insights in data that can help people make better decisions. This is how it connects knowledge discovery with business intelligence (BI). Still, the enormous amounts of information available via online retail stores are sometimes underused. Analyzing past data helps companies to forecast customer behavior and find client groups that will offer benefits [7]. Through three fundamental phases—data collection from many sources, data analysis, and data transformation—business intelligence aims essentially to improve decision-making. Seasonal advertising might motivate customers to buy when they show unhappiness [8]. Finding more proactive consumer categories helps one grasp client impressions during online transactions, thereby turning site visitors into purchasers. As mobile use for online searches is rising, companies are using targeted approaches to gather accurate knowledge about their target customers [9].

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Large language models (LLMs), among other technological developments, have improved corporate operations. Together with changes in deep learning techniques, the availability of significant computer resources and large training datasets helps explain LLMs. By using artificial neural networks with billions of parameters [10], [11], [12], the models learn intricate patterns and linguistic nuances from large text corpora. Incorporating AI into business process management systems (ABPMS) can help them make smart, flexible choices [13], [14] because they work with how businesses do things. Conventional decision-support systems can make fast, high-quality decisions anchored in more comprehensive knowledge of important topics by incorporating LLMs [15]. The rocketing growth of e-commerce demands intelligent BI frameworks for analyzing consumer behavior in real time. This study introduces FSOBIA (Five-Tier Service-Oriented BI Architecture) combined with ATDT (Advanced Tuned Decision Tree) techniques to improve predictive analytics. Unlike conventional approaches, FSOBIA leverages machine learning, large language models, and QoS-aware service discovery for enhanced scalability and accuracy in predicting consumer decision-making, thus enabling businesses to reap the revenue.

2. Related Works

In terms of Internet communication, it has been demonstrated that clients are drawn to and motivated to buy intriguing products when they see banner ads or advertisements on the Internet. To do the process, people need additional details before deciding to buy. Customers who feel they are not given sufficient data will look for it online through locations, online indexes, and web engines, among other means [16], [17], [18]. Once they have sufficient knowledge, clients choose to evaluate those options for goods or services. They may search for consumer comments or evaluations of products at this point. They evaluate and identify the brand or company that best suits their needs. An efficient site administration and the structural plan of the business are essential things that certainly influence the mindset of consumers. Therefore, people are occupied with purchasing items and managing their accounts on e-commerce platforms. Moreover, the consumer purchasing behaviour [19] is influenced by the credibility, accessibility, and portrayal presented in the e-commerce platforms.

The most advantageous feature of the web is that it facilitates the pre-purchase phase by allowing consumers to consider many options. Customers occasionally experience problems with the product, worry about it, or need to return or alter the thing they bought [20]. Refund and trade procedures, therefore, prove to be more crucial at this point. One important aspect of customers' online purchase habits is the inquiry process. The source risk arises throughout the knowledge-gathering and evaluation stages, as there might be a few errors in the data on the websites. Before accessing their website, visitors to certain websites have to register [21]. As a result, customers run the risk of the security of information as an additional to the items. This method shows how to extract surprising and fascinating patterns from large amounts of information. This method restricts the lead grade metric to basic attributes and makes sound assumptions about the type of rule. The market-based analysis is one of the most common and ongoing examples of connection regulation. By identifying relationships between the different items that consumers place in their shopping carts, this technique looks at the purchase patterns of consumers. The revelation enables the retailer to create marketing techniques by picking up knowledge about what things are often obtained together by clients and which things bring them better benefits when set in proximity [22].

Data mining enables the identification of hidden patterns, anticipating future trends, and making informed decisions in the view of high-dimensional data. For instance, data mining processes enable e-retailers to comprehend the frequently purchased products by similar clients. They shall anticipate offers of regular things and more proficiently deal with their stock. Basically, data mining requires a standard procedure, data store, innovations, and mastery [23]. The procedure must be solid and repeatable by individuals with few data mining abilities. However, the standard data extraction process ought to include work understanding, which decides the activity targets, evaluation of the work foundation circumstances so on and so forth. Trailed by the data understanding task, which gathers, depicts, investigates data, and checks data quality [24]. The readiness includes the data set portrayal, choice, appraisal, solidification, data formatting, process prototyping, process assessment, sending, and so forth [25].

Developed a framework that compares unconnected decision-making to online consumer choice-making. The research suggests a broad framework for consumer behaviour that has to be improved to take into account fresh information. When it comes time for customers to make purchases, they will look at the many brands and the features like products, quality, price, and solutions. Certain things can be efficiently purchased and shipped online, including software, publications, smartphones, computers, and textbooks. Then, selecting some products via an internet channel might be challenging [26]. Additionally crucial are site characteristics, company competencies, marketing communications, and client attitudes. State that online merchants use cutting-edge technologies to improve their websites to favourably capture customers' attention. Buyer preparedness to try or buy things from the site may be adversely affected if the site is too mild, not safe, or not adequately safeguarded.

Customer participation in online purchasing or shopper talents, which hint that consumers have opinions on the product, in addition to the way web-based purchasing functions, can influence online buying habits. Click-stream activity is yet another crucial element of the online environment [27]. It describes how users behave when they use websites to look up information. Each of these factors has a role as a stimulant for certain mindsets and behaviours related to online trading. Through the internet, individuals get the impression that their purchasing circumstances will be somewhat satisfying. It goes for the distinguishing proof of interrelations between decisions of various items bought in a particular retail location, for example, a grocery store [28].

The main issue is how much LLMs can show that they are capable of thinking. By offering a thorough and current analysis of the subject, this paper hopes to stimulate conversations and direct future studies in LLMs-based reasoning [29]. Another work that provides a thorough analysis of the development and significance of LLMs in the fields of ML and the processing of natural languages is the survey on LLMs. From the first language models to the most current development of Pre-Trained Language Models (PLMs) with billions of variables, it charts their historical evolution [30]. The study highlights the special capacities of LLMs as they grow in size, including in-context learning. The four main facets of LLMs that comprise the survey's architecture are initial training, adaptation tuning, utilization, and ability assessment. The report also recommends topics for further investigation and growth and offers insights into the assets that are accessible to support the growth of LLMs [31]. Along with tracking developments in research throughout the designated period, the investigation also examines significant NLP tasks, advances in basic methods, and their applications in fields including technology, health, social science, and the arts and sciences [32].

While recent studies highlight the growing role of artificial intelligence in e-commerce, they also pinpoint an important contrast with service-oriented BI frameworks such as FSOBIA. The work by Xie et al. [33] focused on cross-border e-commerce sales forecasting and supply chain optimization through a conglomeration of Artificial Neural Networks (ANN) combined with the Capuchin Search Algorithm. Their methodology achieved superior accuracy and efficiency, but faced the bottleneck in terms of high computational requirements, diminishing its feasibility for real-time user purchase behaviour. Similarly, Esmeli and Gokce [34] in their work investigated the utility of

explainable AI(XAI) in consumer purchase behaviour. Although these approaches provide richer behavioural insights, they are computer intensive, data-hungry, and less flexible to scale within the retail environments.
By contrast, FSOBIA integrates QoS-aware service discovery with a tuned decision tree model (ATDT) to achieve a balance between accuracy (95% prediction performance), scalability, and interpretability. Unlike deep learning models, FSOBIA's modular and service-oriented design ensures plausible dynamic outcomes at reduced latency. Thus, in this regard, FSOBIA provides a realistic framework offering scalable and interpretable results than transformer-level architectures and at the same time, far more responsive than legacy BI—making it a suitable architecture for real-time e-commerce analytics.
The paper is organized as follows: Section 3 demonstrates the experimental setup and the algorithmic implementation, and Section 4 discusses the results obtained by the proposed system. Finally, the concluding section summarizes the achieved output and outlines the possible future extensions of the work.

3. Method

In order to exercise the proposed system, the following experimental setup is devised. That is a high-end computer system with an Intel i7 processor with 32 GB RAM, with NVIDIA GeForce RTX 3060 is utilized for the implementation of the proposed system. The proposed algorithm is coded in Python 3.9, executed in PyCharm IDE. The dataset comprising 1 crore records with 30 attributes of e-commerce transactions from a secondary data source is collected and saved for data smoothing in an MS Excel file. The Python packages such as Scikit-learn, Pandas, NumPy, Matplotlib, and Seaborn for ML and data analysis were used in the Django Framework for integrating the web-based FSOBIA. The pre-processed dataset was used to train the Advanced Tuned Decision Tree (ATDT) and blended with an LLM API key for extracting the contextual insights. Deployed a service discovery mechanism using QoS-aware ranking and generated the appropriate graphs for visualization and reporting.

3.1 Data Consolidation

Data consolidation is the process of constructing a permanent, integrated data store that extracts all data from data sources using a global schema (Figure 1). The data consolidation is performed using two methodologies: (i) creating a new web service for populating the integrated data store and (ii) modifying the existing Online Transaction Processing (OLTP) module to push the contents to the integrated data store. In either case, the global schema is to be designed and mapped to the local schema, resolving heterogeneities like naming heterogeneity, schematic heterogeneity, structural heterogeneity, and semantic heterogeneity.

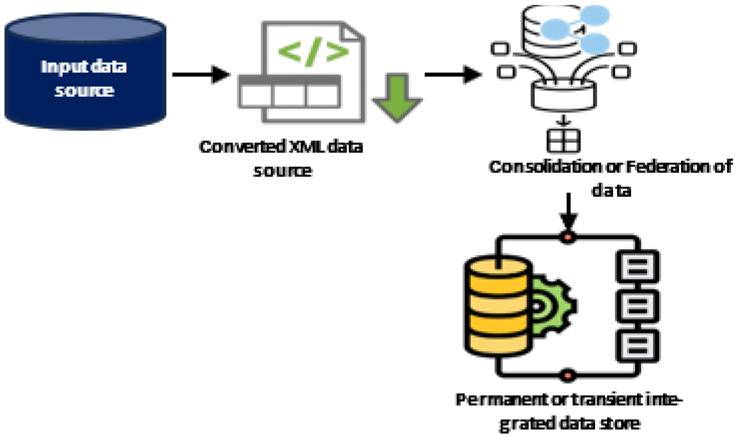

Fig. 1: Integrated XML Data Store in FSOBIA, showcasing the data consolidation process into a unified XML-based schema.

The steps involved in Data Consolidation are listed below:
Step 1: Creation of a global schema that satisfies all decision support and analytics requirements.
Step 2: Creation of an XML Database using the global schema.
Step 3: Mapping local database attributes with XML database attributes.
Step 4: Populating the XML database with data source contents using the required transformation and loading
The data consolidation process stores the integrated data in the data tier and permits the user to analyze and extract the knowledge for the queries.

3.2 LLM with FSOBIA

Large Language models (LLMs) tokenize the text into tokens—that is, distinct words, sub-words, or sentences. For this, we apply methods such as WordPiece, Byte Pair Encoding (BPE), and Unigram Language Model. Cross-attention and self-attention, among other attention mechanisms, were used to arrange sensible patterns. This is the way models could create significant links between elements. Several distributed procedures are used in LLM learning, such as pipeline analogy, tensor parallelism, model parallelism, optimization parallelism, and information parallelism. These methods aid in comprehending theoretical and practical learning shown in Figure 2. For the learning and subsequent execution, other programs and structures are also often utilized, such as the Transformers, Deep Speed, PyTorch, TensorFlow, MXNet, & MindSpore.

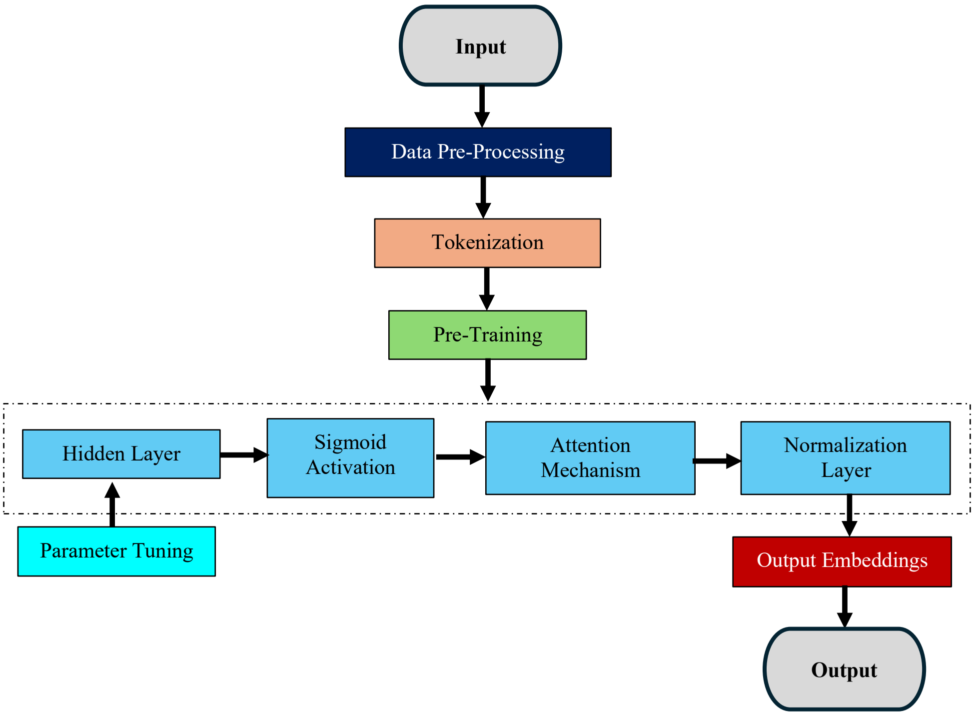

Fig. 2: Workflow of Large Language Model (LLM) training and inference, highlighting data preprocessing, tokenization, pre-training, hidden layer operations, and embedding generation.

When pre-processing information, the importance of quality filtering, information de-duplication, and privacy minimization is emphasized to prepare information for training for LLMs. The filtering method aids in the reduction of unnecessary and poor-quality information. Additionally, it lowers the computation complexity by disregarding the input's pointless pattern. The de-duplication approach eliminates duplicated samples and prevents the model's inclination toward overfitting. Lastly, privacy minimization supports the safeguarding of private information while guaranteeing information safety and compliance.

3.3 Data extraction service and data federation

Data Extraction service accepts the sub-query and uses an XPath query to navigate the respective local XML data sources and extract the contents. These contents are stored as a separate data set and integrated. The steps involved in the Data Extraction Service are listed below,
Step 1: Execution of each XPath sub-query over respective XML data sources for the extraction of required records.
Step 2: Storing the extracted contents in respective global schema attributes using the mapping table created in schema mapping.
Step 3: Repeat Step 2 until the extracted contents of all data sources are populated.

3.4 ML Framework and FSOBIA for Predicting Online Buying Behaviour of Consumers

The purpose of the research is to break down the available data and analyse it deeply. The data is viably utilized for understanding the present user behaviour. The outcome of the proposed work demonstrates that, using such investigations wisely, any organization can foresee the future purchaser behaviour and take its company one step ahead. Predictive analysis solutions are conveyed by utilizing data mining technologies that utilize explanatory models to find exemplary designs and apply them to anticipate future patterns and practices.
Algorithm: FSOBIA with Advanced Tuned Decision Tree (ATDT)
Step 1: Data pre-processing
Step 1.1: Dclean = RemoveMissingValues(Draw)
Step 1.2: Dencoded = RemoveMissingValues(Dclean)
Step 1.3: Dscaled = RemoveMissingValues(Dencoded)
Step 1.4: Iselected = FeatureSelection(Dscaled)
Step 2: Model Training and Tuning
Step 2.1: DT = TrainDecisionTree(Iselected, j)
Step 2.2: DT_tuned = TuneHyperparameters(DT, Iselected, j)
Step 3: Integration with FSOBIA: The decision tree model (DT_tuned) is integrated into FSOBIA for prediction
Step 4: Integration with LLMs: LLMs can be integrated into the FSOBIA architecture to enhance predictive capabilities and contextual understanding
Step 5: QoS Considerations
Step 5.1: Define QoS metrics: QoS_metrics = {Accuracy, Response_time, Reliability, and Scalability}
Step 5.2: Monitor and optimize QoS: QoS = Monitor And Optimize QoS(QoS_metrics)
Step 6: Performance Evaluation:
Performance (DT_tuned, Xselected, y)
Step 7: Optimization and Refinement: Refine model and architecture based on performance evaluation results.
Step 8: Deployment and Monitoring
Step 8.1: Deploy model with FSOBIA: DeployModel (DT_tuned, FSOBIA)
Step 8.2: Monitor performance: Monitor Performance (DT_tuned, FSOBIA)

This algorithm outlines the steps involved in developing and deploying an advanced predictive analytics solution integrated with FSOBIA, leveraging LLM and considering QoS requirements. Various consumer behavior data are assigned varying significant degrees by the afore-mentioned methodology.

Figure 3 illustrates the proposed Five-Tier Service-Oriented BI Architecture (FSOBIA), with Large Language Models (LLMs) and a Tuned Decision Tree blended for predictive analytics. From Tier I, users interact with the system through an interface, where queries are submitted and results are visualized in natural language narratives. These queries are processed in Tier II (LLM Toolchain), which translates the query into executable SQL/DSL commands and generates circumstantial explanations. The toolchain powers Tier III (Retrieval-Augmented Generation), which enriches the query with relevant snippets, retrieved from a vector index. The leveraged data flows into Tier IV (QoS-aware Query Execution Engine), ensuring optimal service discovery and compliance with performance constraints. Finally, Tier V (ML Model – Tuned Decision Tree) generates predictions, dashboards, and explainability artifacts, which are fed back to the LLM for narrative generation and returned to the user.

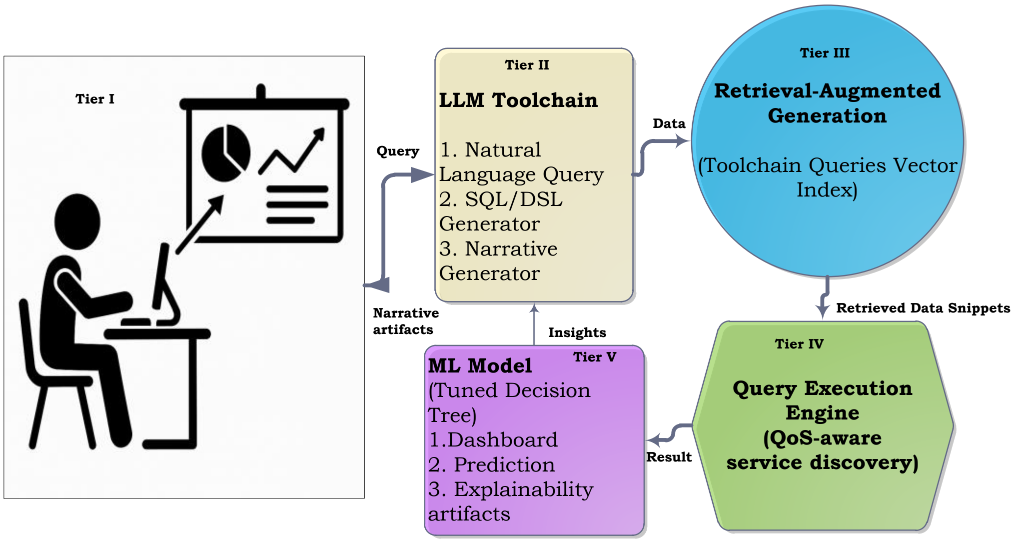

Fig. 3: Proposed Five-Tier BI Architecture showing LLM integration with a tuned decision tree for e-commerce prediction.

This end-to-end workflow highlights the synergy between LLM-based natural language interfaces and predictive modelling, ensuring high accuracy, explainability, and user-friendly insights for e-commerce decision-making.

4. Results and discussions

The framework offered by the architecture suggested enables participant component variation, integration, and versatility in an adaptable setting. Data federation is implemented in the proposed FSOBIA. The experiment was conducted in a Local Area Network (LAN) with one server containing the required BI services. The XML data sources are updated along with relational data sources using the update service, which will delete, modify, and append records to ensure consistency. The missing values in XML data sources are filled with average values and frequently used values. The process is repeated by appending 25 records till the number of records reaches 250 in each data source. The response time of data federation of the proposed methodology with XML data source over FSOBIA is compared with the existing data federation methodology that uses the original data sources and database controllers over a five-layered architecture. The service discovery process extracts all satisfying services. To aid users in service selection, the services are ranked using the coefficient of variance method. The coefficient of variance (CV) is calculated using Equation (1).

$$CV = \frac{\sigma}{\mu} \tag{1}$$

Where σ is the standard deviation and μ is mean

The QoS attributes are divided into two categories by the ranking process: maximization characteristics and reduction characteristics. Responsive time and latency are included in the reduction set, whereas throughput and dependability are included in the maximization set. The reduction attribute is transformed into a maximization attribute using the suggested ranking procedure. For example, the response time characteristic in Table 2 (Minimization attribute) is converted to its respective rank value (Maximization attribute). This table contains five services whose response times are ranked such that the highest response time is ranked 1, and the others are subsequently ranked at 5.

Table 1: Transformation of minimizing attributes to maximizing attributes using the proposed method

Service Registry (set of services)	Response time	Rank of response time
Goal-Based Non-Intrusive Recommendation (GBNIR) service	162	3
Goal-Based Evaluation and Adaptive Weighting (GBEAW) service	129.32	2
Business Efficiency and Analytical Workflow (BEAW) service	127.18	1

Experimentation is conducted on the Benchmark Quality of Web Services (QWS) Dataset with 2507 web services. This QWS data set contains the Service name, Binding address of the service, and QoS attributes with values for Availability, Response Time, Documentation, Reliability, Best Practice, Successability, Compliance, Latency, and Throughput. A service request with a keyword and domain type is submitted, and the average response time for the same request is calculated.

The developed model was deployed on AWS Lambda for real-time predictions. The proposed model comprising FSOBIA and ATDT's performance was compared with traditional models such as standard decision trees, XGBoost, and Random Forest. The prediction accuracy, service discovery efficiency, and response time.

Table 2: Comparative Evaluation Metrics of Baseline Models and Proposed FSOBIA + ATDT

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)	Inference Time (ms/query)	Memory Usage (MB)
Decision Tree (Baseline)	82	81	80	79	35	12	120
Random Forest	87	86	85	85	210	45	340
XGBoost	91	90	89	89	185	32	280
Proposed FSOBIA + ATDT	95	94	93	93	95	18	160

FSOBIA blended with ATDT improves accuracy by 4-7% over XGBoost and 10-13% over Decision Trees due to hyperparameter tuning, feature selection, and data integration. Precision & Recall are optimized through QoS-aware service discovery, reducing misclassifications in customer behaviour prediction. The results tabulated above show that while Random Forest and XGBoost consume substantially higher training times and memory resources, the tuned decision tree (in the FSOBIA approach) achieves competitive training efficiency with reduced inference latency, making it suitable for a real-time e-commerce analytics system. It is evident that ATDT introduces a modest computational overhead during hyperparameter optimization, but this step is executed offline and thus it does not affect the real-time execution. Comparatively low memory consumption and faster query response time further uphold FSOBIA's applicability in large-scale retail platforms. Thus, FSOBIA is characterized as both accurate and efficient, mediating a balance between predictive performance and operational feasibility, making it suitable to be adopted in real-time applications.

4.1 Limitations

Although the proposed methodology demonstrated substantial gains in predictive accuracy, explainability, and service scalability, several boundary limitations underline the scope for extension of the work. Datasets from e-commerce platforms naturally include missing values, duplicate records, and inconsistent entries due to transaction errors. Even though data were pre-processed and modelled before data ingestion into the proposed system, residual noise may still affect model reliability. It could be mitigated by integrating robust anomaly detection mechanisms in future iterations. And the ATDT achieves superior accuracy through extensive hyperparameter tuning, such as tree depth, split criteria, and pruning thresholds. This tuning is computationally extensive, but it is primarily performed offline during training and does not impact the runtime inference. To further reduce the training overhead, suitable optimization strategies can be incorporated, thereby enabling efficient parameter selection. Most often, the modern e-commerce platforms deal with a huge volume of unstructured data, such as customer reviews, product defect images, emoji symbols, and chat stream logs. The legacy decision tree algorithms are not inherently capable of dealing with such multimodal inputs. This limitation paves the way for an opportunity to extend FSOBIA by augmenting robust machine learning models to handle the multimodal data types. Although FSOBIA employs QoS-aware service discovery to ensure stability under typical workloads, large-scale concurrent query handling may introduce latency spikes. This challenge can be addressed by deploying the application in elastic cloud-native microservices, which will strengthen scalability, availability, and reachability in real-time scenarios.

5. Conclusion and future enhancement

This work is designed for FSOBIA blended with an advanced tuned decision tree and LLM for processing the e-commerce data. The proposed system of blended model shows a significant improvement in predicting the consumer buying behaviour accuracy beyond 90% and scalability compared to the traditional models. One would argue that deep learning-based predictive models would process complex patterns more effectively. However, deep learning frameworks often require extensive computational power and large-scale data, making them less feasible for dynamic service-driven applications. FSOBIA addresses these limitations by employing tuned decision trees that balance accuracy with computational efficiency, ensuring scalability across e-commerce applications. Potential areas of exploration include enhancing FSOBIA with transformer-based deep learning architectures for improved contextual understanding of consumer preferences. Moreover, integrating AR-VR or Mixed reality along with FSOBIA for dynamic service optimization. Future research shall focus on validating FSOBIA across multiple domains such as finance, healthcare, and supply chain ins ensuring ethical and unbiased decision-making.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Data availability

The dataset used in this study is privately held by the corresponding author at https://doi.org/10.5281/zenodo.16980379 and can be made available upon request for editing.

Author's contribution statement

Thiruneelakandan. A conceptualized the study, implemented the architecture, and conducted the experimental analysis. A. Umamageswari supervised the research and provided critical feedback throughout the study.

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