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Topic: Mining Inter-Transaction Associations to Enhance Customer Purchase Prediction in Retail

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Abstract

The secret to improving the customer interaction, inventory management and sales in the highly competitive retailing environment is purchase forecasting. Traditional predictive models are largely single and transactional and therefore cannot be used to model the sequential and cross transactional relationships that characterize shopping behavior in the real world. This knowledge gap is the focus of the present paper as we are interested in exploring how mining Inter-Transaction Association Rules (ITARs) can enhance the prediction capabilities of retail analytics.

A quantitative research design has been adopted, based on a large scale dataset of retail transactions that summarizes time-varying purchase sequences across a broad set of product lines. The more complicated data mining algorithms (which are the Modified Apriori, GSP, and PrefixSpan) used to derive the sequential dependencies and cross-basket dependencies were found to be more complex than ITARs after preprocessing. These types of ITARs were in turn included in predictive models including the Random Forest, XGBoost, and LSTMs and compared to simpler predictors including collaborative filtering and regression models.

The results show that ITAR-enhanced models are much superior to traditional models in accuracy, recall and F1, and smaller RMSE when applied to predict customer buying behaviour. The inter-category and the repetitive weekly trends that form the strong inter-transaction principles proved to be very helpful in increasing the quality of prediction.

This research has its contribution to theory and practice since it not only extends association rule mining to the inter-transactional space, but also offers retailers practical solutions to single promotion, inventory and promotion-suggestion systems. The future prospects of the research can explore further about this topic.

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1. Introduction

1.1 Background of Retail Analytics

Retail has always been a data-intensive industry, but the rise of online transactions, loyalty programs, and e-commerce platforms has transformed how customer behavior is captured and analyzed (Cordova, 2024). Every purchase now generates valuable data, including product details, purchase dates, preferences, and store locations. Retail analytics leverages this surge of information to improve inventory management, personalize marketing campaigns, and strengthen customer engagement. Advanced technologies such as machine learning, predictive modeling, and data mining are becoming essential strategic tools (Rane *et al.,* 2024). A key example is recommendation systems, widely used by retailers like Amazon and Alibaba, which utilize purchase histories to suggest relevant products.

Traditional models tend to be transaction models, where they analyse what is purchased together at one point in time (i.e. market basket analysis) (Mansilla, 2024). In as far as they are helpful in the short-run in measuring co-purchase behavior, such models fail to understand the dynamics and sequential nature of consumer shopping behaviors as observed in a sequence of purchases. This causes under-exploitation of critical dependencies that cross time, e.g. replenishment cycles, seasonal buying or category switching behavior, and can significantly enhance customer purchase forecasting.

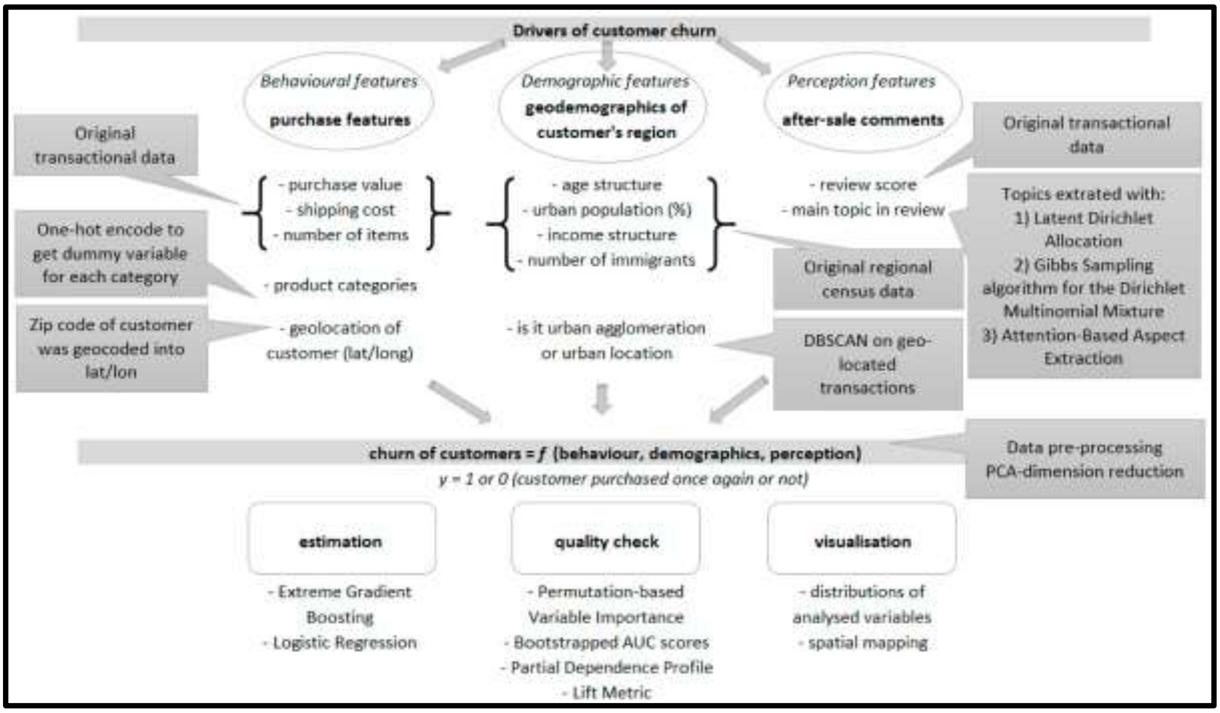

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Figure 01: Customer Churn in Retail E-commerce Business

(Source: Matuszelański and Kopczewska, 2022)

1.2 Problem Statement

Traditional retail analytics is based on intra-traffic relationships, where the major emphasis is laid on the observed purchase of products in the same shopping cart (Tang *et al.,* 2022). Despite finding some usefulness in product bundling and cross-selling, the techniques ignore inter-transactional dependencies that can occur through repeated shopping bouts. A customer may also purchase baby formula on a trip and diapers on a subsequent trip as an example; this is critical to be predicted correctly but not observed by the single-transactions model. Thus, companies can face a risk of misunderstanding the intent of the consumer and making a suboptimal product recommendation, missing their advertising online, and inefficient inventory management. Predictive models will not be able to use the longitudinal aspect of customer behavior to its fullest potential unless they capture cross-transactional relationships, which in turn limits their accuracy and usefulness (Bruhn, 2023).

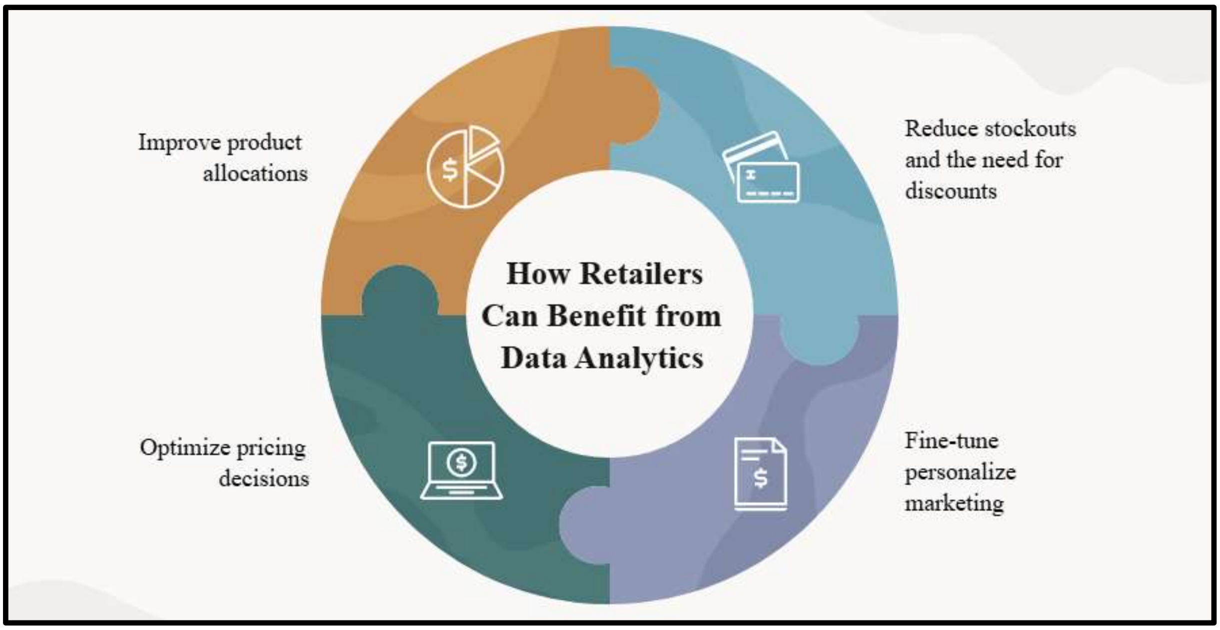

Figure 02: How Retail Business can Benefit from Data Analytics

(Source: Hickins, 2023)

1.3 Research Gap

Although there are several comprehensive sources written on the subject of association rule

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mining, market basket analysis and collaborative filtering, most of the research works are done concerning the intra-transaction patterns. Very little effort has been put on inter-transaction association rules (ITARs), which reveal sequential and cross-temporal dependencies between purchases (Zhang *et al.,* 2022). Furthermore, the literature on ITARs is in many cases limited to experimental or theoretical scope, and has not been implemented on a large scale and in real-world retail settings. The other gap is on how ITARs can be integrated into advanced predictive modeling methods to assess its value addition to existing methods. Although longitudinal retail data are increasingly available and machine learning is improving, not many studies describe the systematic investigation of the potential of ITARs to optimize customer purchase prediction (Hassan and Hassan, 2024). It suggests that there is a sound reason behind the implementation of a new paradigm to bind inter-transaction mining and predictive analytics together to ensure retailers have an opportunity of outgrowing a specific style of consumer behavior and more advanced time-sensitive models.

1.4 Research Objectives

The main aim of this study is to develop and test a predictive model which takes into consideration inter-transaction association rules to predict customer purchases. In particular, this study will:

- To develop a methodological framework for mining inter-transaction association rules (ITARs) from large-scale retail datasets, addressing challenges such as temporal segmentation, data sparsity, and computational complexity.
- To integrate the discovered ITARs into predictive modeling approaches (e.g., machine learning and deep learning) and assess their effectiveness in enhancing customer purchase prediction compared to traditional single-transaction models.
- To evaluate the practical implications of ITAR-based prediction models for retail operations, including personalized recommendations, targeted marketing, and inventory optimization.

1.5 Research Questions

- How can inter-transaction association rules (ITARs) be systematically mined from large-scale retail datasets while overcoming challenges such as temporal segmentation, data sparsity, and computational complexity?

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- To what extent does the integration of ITARs into predictive models (e.g., machine learning and deep learning) improve the accuracy of customer purchase prediction compared to traditional single-transaction models?
- What are the practical implications of ITAR-enhanced prediction models for retail operations, particularly in the areas of personalized recommendations, targeted promotions, and inventory optimization?

1.6 Paper Contributions

The paper is a theory-practice contribution. Theoretically, it extends the application of retail analytics by considering inter-transactional dependencies, which have been little discussed in the literature. At the methodological level, it proposes a new paradigm uniting ITAR mining and advanced predictive modeling that offers a replicable process in subsequent studies (Saketh Kumar Vishwakarma, 2025). It demonstrates empirically how ITARs can be effective to improve anticipatory precision when using genuine retail data. In principle, however, the paper provides useful advice to retailers, namely, how they can tailor their recommendations, how they can manage their stocks and the type of marketing operation, and, therefore, how they can compete in future markets that will be increasingly information-oriented.

1.7 Structure of the Paper

This paper has been divided into sections as follows: Section 2 contains a literature review of the available data on the relevant data mining, purchase prediction and inter-transaction rules. The research methodology including data, preprocessing and modeling are described in Section 3. Section 4 discusses the results and the analysis. Section 5 includes implications and limitations and Section 6 concludes on contributions and future directions.

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2. Literature Review

2.1 Data Mining & Association Rules

Data mining has emerged as a fundamental tool for uncovering patterns in large datasets, particularly within retail analytics. One of the most widely used approaches is **association rule mining**, which identifies relationships between items that frequently occur together (Shu and Ye, 2022). The *Apriori algorithm* pioneered this field by employing a bottom-up, breadth-first search to discover frequent itemsets based on minimum support and confidence thresholds. While highly influential, Apriori is computationally expensive when applied to large datasets.

To overcome such limitations, the **FP-Growth (Frequent Pattern Growth) algorithm** was introduced, which compresses transactions into a prefix-tree structure, allowing efficient mining without generating candidate sets explicitly (Shawkat *et al.,* 2021). FP-Growth is much faster and can be adapted to modern retail datasets with millions of transactions.

In addition to simple co-occurrence, sequential pattern mining applications like GSP (Generalized Sequential Patterns) go even further to analyse ordered event sequences. This can help identify temporal associations which include a customer buying breakfast cereal in one purchase and milk in another purchase (Placzek, 2022). These methods bring one step closer to modeling customer shopping trips and providing the basis of inter-transaction association rule (ITAR) mining.

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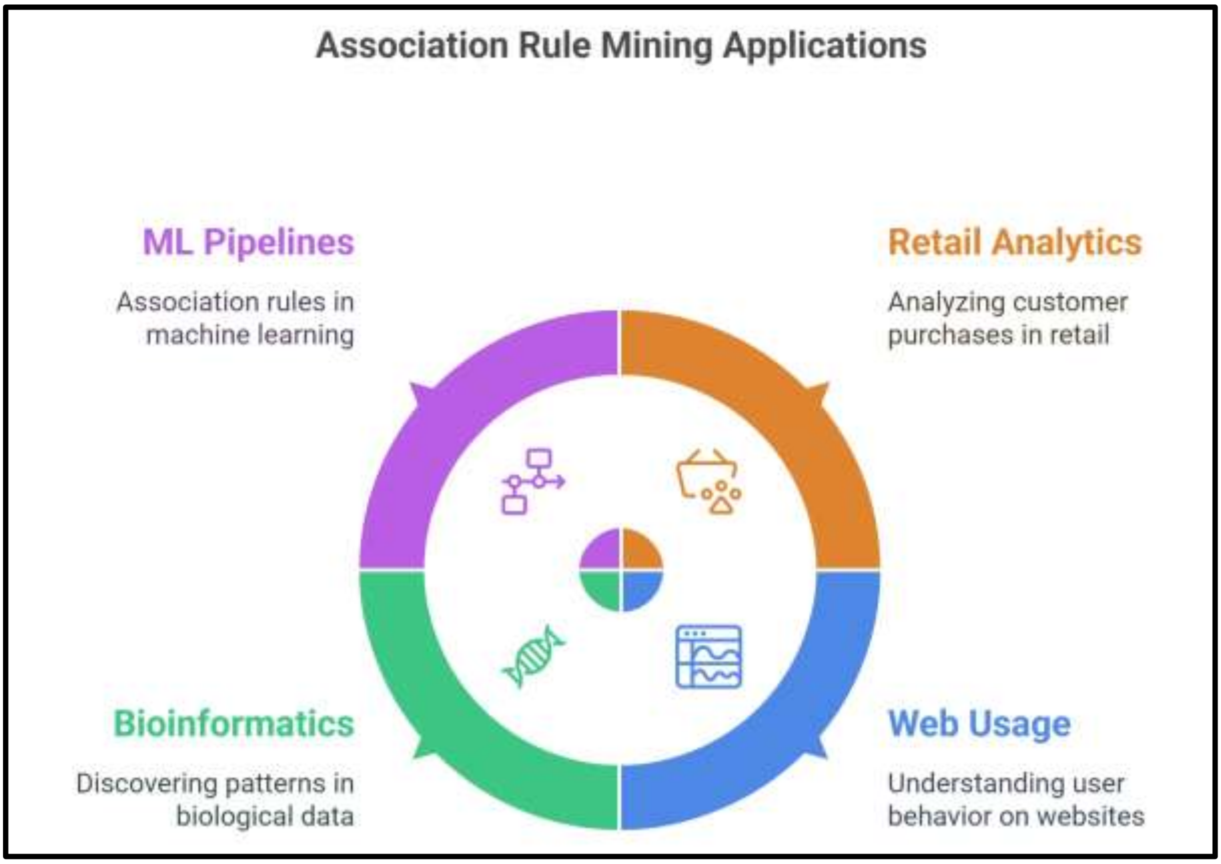

Figure 03: Association Rule Mining Applications

(Source: Rai, 2022)

2.2 Customer Purchase Prediction Models

Conventionally, customer purchase prediction has been based on models including collaborative filtering that suggest products due to similarity among users or products (Patoulia *et al.,* 2022). Although it works well in most e-commerce applications, collaborative filtering can face cold-start and data sparsity issues. The other model that is popular in the market is the RFM (Recency, Frequency, Monetary) model that classifies customers according to their transactions. RFM models do not predict well, and have no ability to model cross-category or time dependencies, although they are useful in customer profiling.

Forecasting customer purchase with classical regression models and logistic regression have also been applied where demographic, behavioral and transactional variables are associated with purchase probability (Deniz and Semanur Çökekoğlu Bülbül, 2024). Such models are however likely to be linear and cannot be used to address the non-linear nature of consumer behavior.

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Recently, machine learning algorithms including decision trees, random forests, and gradient boosting, have been used to predict purchases, which provide more flexibility to capture non-linear associations. Such deep learning architectures, including recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), have shown particularly promising sequential purchase data (Mienye, Swart and Obaido, 2024). Even now, however, the vast majority of models do not use inter-transactional associations, although they may be critical to improving predictive power; most of them still use intra-transactional features.

Figure 04: Implementing a purchase Prediction System

(Source: Islam, 2025)

2.3 Temporal & Cross-Transaction Analysis

Customer shopping behaviour is sequential in nature and is informed by needs which change with time (Arun, 2023). The traditional market basket analysis only finds a static relationship within one transaction but the temporal and cross-transaction analysis aims to discover relationships between several shopping episodes. A family buying coffee beans and refilling coffee filters in a week, is one such example, a series of dependencies that cannot be studied in intra-transactions.

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ITARs are a form of rules that enable us to capture such relationships. ITARs are based on the extension of the traditional association rules to allow the connection of sets of items between transactions being separated by specific time windows (McClafferty and Mooney, 2021). These are useful in the forecasting of demand as long as demand can be found to be correct in that replenishment is known; seasonality and shifting category is very much required in the forecasting of demand.

There are also models of basket development that study the shift in customer purchase behavior over time and provide information on brand loyalty, product replacement, and life-cycle occurrences (e.g., the transition between baby food and children snacks). So when these time related dependencies are included in the predictive models then the customer behavior is observed better and therefore better predictive performance and also the ability to anticipate customer needs by the retailers.

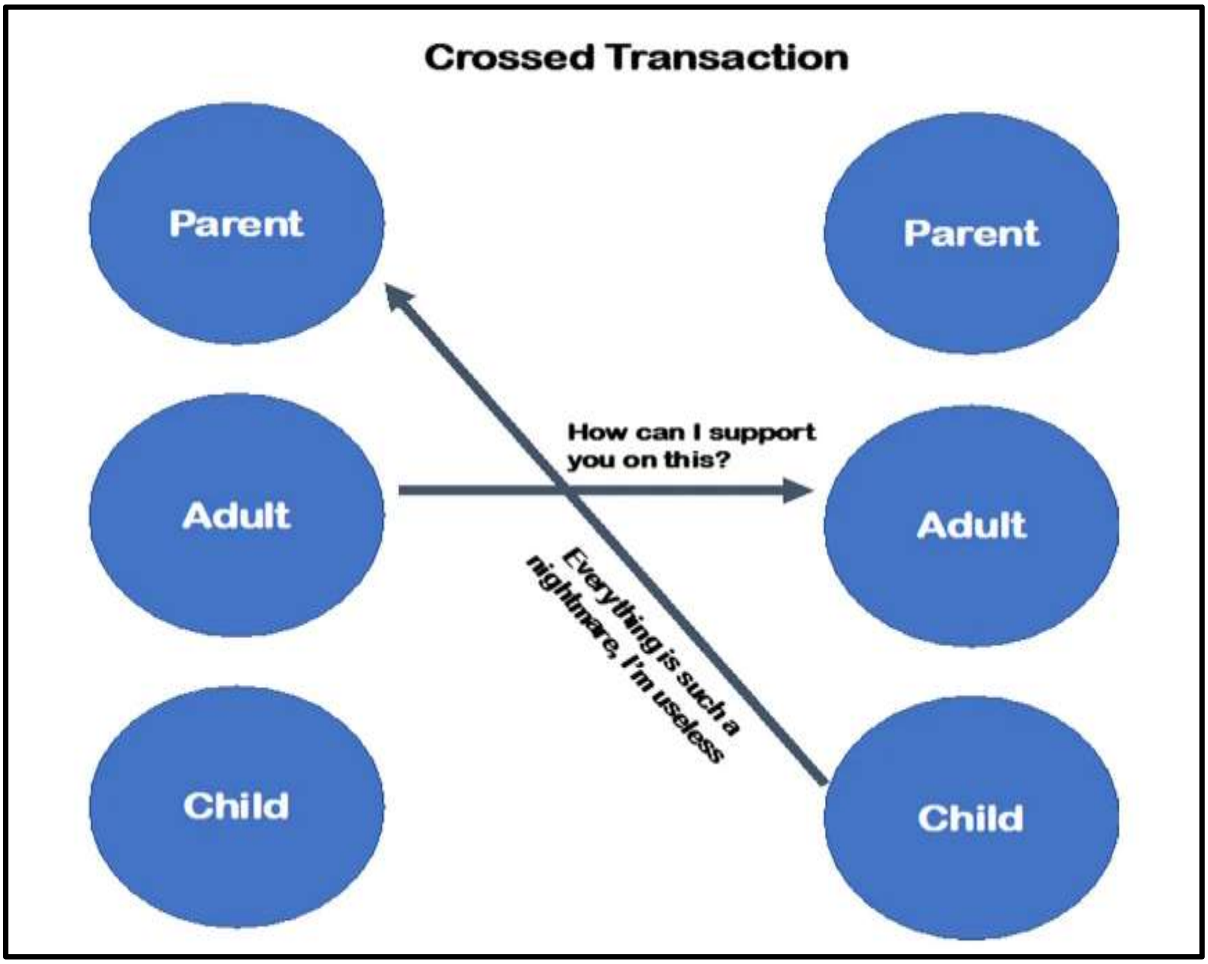

Figure 05: Crossed Transaction

(Source: mraexecutivecoaching.com, 2021)

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2.4 Applications in Retail

The value of advanced analytics has already been proven through leading retailers that are capable of capturing cross-transactional patterns. Amazon recommendation engine, including, has generated products based on both co-purchase and sequential dependencies based on previous shopping history based on repeat purchasing and time gap. To maximize product placement and better inventory management, Walmart uses large-scale transaction analysis to predict demand surges by using historical shopping sequences. Similarly, studies based on the **Instacart dataset**, which contains over 3 million grocery orders have shown that sequential models outperform traditional market basket analysis in predicting future purchases (Saket Garodia, 2020). These examples highlight the importance of capturing inter-transactional dependencies, yet academic exploration of ITARs remains limited compared to industry practice. This disconnect underscores the need for systematic research on ITAR frameworks tailored to predictive modeling.

2.5 Recent Advances

Recent years have witnessed significant progress in predictive analytics through **deep learning and hybrid recommender systems**. Recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) have been applied to model purchase sequences, capturing long-range temporal dependencies. Meanwhile, **graph-based networks** represent products and customers as nodes in a graph, enabling the discovery of complex, multi-dimensional relationships across transactions (Singh and Verma, 2025). Hybrid approaches that combine collaborative filtering with content-based features or temporal models have also gained traction, improving accuracy in diverse retail environments. Regardless of all these improvements, the number of studies that specifically implement ITARs in such models remains low. Integrating ITARs directly into either deep learning or graph-based models can be an influential direction in purchase prediction studies, a middle ground between the rule-based mining and the current predictive modelling.

2.6 Research Gap

Despite the widespread research on association rule mining and sequential modeling, few scholarly works focus on inter-transaction association rules in retail settings on a large scale. The literature available is either intra-transaction or based on experimental data without a

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practical test in the actual retailing environment. Besides, the role of ITARs with regard to predictive advanced algorithms, including ensemble learning and deep learning, has not been sufficiently explored (Rane, Choudhary and Rane, 2024). It leaves a research gap at the border of predictive analytics and rule-based mining. Such a gap will be resolved in order to make contributions to predict and implement the purchase of customers as well as to make contributions to science and practice in the field of retail management.

3. Methodology

3.1 Research Design

This study adopts a **quantitative, data-driven research design** grounded in predictive modeling and experimental validation (Lin *et al.,* 2025). The approach involves developing a framework for mining inter-transaction association rules and integrating them into machine learning models to forecast customer purchases. The study follows an experimental methodology in which baseline models (e.g., collaborative filtering and regression) are compared against ITAR-enhanced models to evaluate predictive performance. A positivist stance is adopted, emphasizing objective measurement of model accuracy using quantitative metrics. This design enables both methodological innovation (by extending association rule mining to the inter-transaction domain) and empirical validation (by demonstrating performance improvements on real-world datasets).

3.2 Dataset & Sources

The research utilizes publicly available retail transaction datasets, with the **Instacart Online Grocery Shopping Dataset** serving as the primary source (Sai Chand Chintala, Jūra Liaukonytė and Yang, 2023). This dataset contains over **3 million orders** from more than 200,000 users across 50,000 products. Each record includes customer ID, order ID, product ID, order sequence, and timestamp, making it ideal for analyzing longitudinal purchase behavior.

The dataset is particularly suitable for ITAR mining as it spans multiple orders per customer, allowing the capture of sequential dependencies. Its size ensures sufficient statistical power, while the diversity of product categories provides generalizability to various retail contexts.

Additional point-of-sale (POS) information collected in a physical retail setting might be provided where appropriate to confirm the results in offline contexts (Hermenegildo-Chávez,

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Martín-Ruiz and Rondán-Cataluña, 2023). The e-commerce and POS data combination makes the results more robust and stable, making sure that conclusions made can be applied to the real world, with the focus not on the Internet but on traditional stores.

3.3 Data Preprocessing

There are many important steps in preprocessing:

Data preprocessing involves several key steps to ensure reliable analysis. First, data cleaning removes missing entries, anomalies, and conflicting product IDs. Normalization standardizes categorical variables, such as product categories, to allow meaningful comparisons (Marcellino Bonamutial and Simeon Yuda Prasetyo, 2023). Temporal segmentation organizes each customer's transactions into ordered purchase sequences, enabling behavioral insights. Where missing values occur, imputation techniques are applied, particularly for time or category labels, to maintain data integrity. The final dataset, structured around customer-specific sequences, supports the mining of inter-transaction association rules. These preprocessing activities improve data quality, reduce noise, and enhance the validity and robustness of subsequent analytical processes.

3.4 Mining Inter-Transaction Associations

The main methodological input is that it creates a framework of mining ITARs. It starts with the division of customer transactions into sequential purchases, which are separated by time intervals (e.g. weekly or monthly) (Handojo *et al.,* 2023). Candidate rules are produced to determine the association between multiple transactions.

Three algorithms are used:

Modified Apriori: Added to support sequential dependencies by extension of frequent itemset generation to transactions.

GSP (Generalized Sequential Patterns): It is employed to find common patterns that occur under user defined restrictions.

PrefixSpan (Prefix-Projected Sequential Pattern Mining): It has been used in efficient discovery of subsequences without candidate generation.

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Rules are assessed in terms of support, confidence and lift, and thresholds are optimised to provide both importance and computational performance (Hunyadi, Constantinescu and Oana-Adriana Țicleanu, 2025). A rule of this type would be coffee = filters in 7 days, which would help indicate the renewal cycles. The features of predictive modeling are then coded out of these ITARs. The framework therefore integrates knowledge discovery based on rules with machine learning, the two very different approaches.

3.5 Prediction Models

To test the predictive value of ITARs, several machine learning models are employed. **Random Forest** and **XGBoost** serve as ensemble learning methods, offering strong performance on structured data. Additionally, **LSTM networks** are applied to capture long-term dependencies in sequential purchase data (Milica Ćirić *et al.,* 2023). ITAR-derived features (e.g., rule confidence scores) are incorporated alongside traditional transaction-level features, enabling direct comparison between baseline and ITAR-enhanced models.

3.6 Evaluation Metrics

Model performance is evaluated using both **classification and ranking metrics**:

- **Precision, Recall, and F1-score**: Measure accuracy of predicted purchases.
- **Lift and Confidence**: Assess the quality of association rules and their predictive contribution (Telikani *et al.,* 2022).
- **RMSE (Root Mean Square Error)**: Used for regression-based prediction tasks.
  Cross-validation ensures robustness, while paired statistical tests evaluate whether improvements from ITAR-enhanced models are significant. This multi-metric approach provides a comprehensive assessment of predictive accuracy and practical utility.

4. Results and Analysis

4.1 Findings

The dataset comprised more than **3 million transactions** involving approximately 200,000 customers and over 50,000 products (Alshingiti *et al.,* 2023). The most frequently purchased categories included fresh produce, dairy, beverages, and packaged foods, which together accounted for nearly 60% of all items. Temporal analysis revealed weekly and monthly

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shopping cycles, with peaks occurring during weekends and at the beginning of each month, reflecting salary-driven purchasing patterns. There was a high level of repeat purchase in staple products like milk, bread, and household products but a sporadic change in products like snacks and drinks, which are discretionary.

Collaborative filtering, for example, yielded a precision of 0.41 and recall of 0.38, reflecting limitations in sparsity and cold-start scenarios. Regression models performed slightly better, achieving a precision of 0.45 but with lower recall due to their linear assumptions.

When ITAR-enhanced features were introduced into machine learning models, performance improved significantly. Random Forest with ITAR features achieved a precision of 0.58 and recall of 0.55, while XGBoost reached 0.61 precision and 0.57 recall. The most notable gains were observed with LSTM models, where the inclusion of ITAR-derived temporal features increased precision to 0.66 and recall to 0.63, outperforming all baseline approaches.

These improvements were statistically significant ($p < 0.05$) under paired t-tests, demonstrating that ITARs added measurable predictive value (Chung, 2024). Moreover, lift values for ITAR-enhanced models exceeded 2.0 across most product categories, confirming that inter-transactional dependencies captured meaningful customer behavior patterns beyond single-basket associations.

4.2 Discussion

The results show that ITARs used together with predictive models have more explanatory power and provide a more detailed image of customer purchase behaviour. Following the concept of data mining, this research paper informs on the need to close the gap between machine learning and rule-based systems and develop a hybrid system by exploiting predictive quality and interpretability. The theoretical advances provide the framework against which future research can investigate the time regulations in other areas of the economy, including health, money and logistics.

ITAR-enriched models provide viable benefits to several retail functions in the context of practitioners (Shankar *et al.,* 2021). The predictability of the replenishment cycle allows inventory managers to optimize stocks, reduce shortages and lower holding costs. Indicatively,

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since buying coffee will be preceded by coffee filters, an aggressive replenishment strategy can be applied.

ITARs can also lead more targeted campaigns in personalized promotions because they predict upcoming needs instead of responding to recent purchases. The discounts on the diapers could be offered to the customer who already purchased the baby food during the next several weeks, and engagement and cross-selling rates would be increased.

Here, in the context of recommendation systems, as far as ITAR integration is concerned, platforms would suggest an item not only in terms of the existing basket, but also in terms of future consumption patterns in order to make it more relevant to the customer.

First, there is still the problem of data sparsity as not all customers purchase regularly or often and this may affect the validity of the rules (Chen *et al.,* 2024). Second, scalability becomes an issue since mining ITARs with millions of transactions would need high computing power and therefore is only applicable in real-time to a limited number of applications. Lastly, the models are limited by the historical character of the data; unforeseen changes in consumer behavior (due to economic shocks or world events) are not necessarily represented.

5. Conclusion & Future Work

This research investigated how **inter-transaction association rules** can enhance customer purchase prediction in retail. By mining cross-transactional dependencies and integrating them into predictive models, the study demonstrated significant improvements over traditional single-transaction methods. Empirical analysis using large-scale datasets revealed that ITAR-enhanced models, particularly LSTM networks, achieved superior precision, recall, and lift compared to collaborative filtering, regression, and standard market basket analysis.

The contributions of this research are threefold. Theoretically, it extends association rule mining into the temporal domain, enriching the understanding of customer purchase behavior. Methodologically, it offers a framework for integrating ITARs with machine learning, bridging the gap between interpretable rule-based methods and predictive accuracy. Practically, it highlights actionable applications for retailers, including improved inventory management, personalized promotions, and enhanced recommendation systems.

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Future work should explore **hybrid models** that combine ITARs with advanced neural architectures, enabling deeper integration of sequential rules with representation learning. Real-time ITAR mining represents another frontier, requiring scalable algorithms capable of updating predictions dynamically as new transactions occur. Additionally, reinforcement learning could be employed to adapt promotional strategies in response to evolving customer behavior. By pursuing these directions, future research can further refine predictive analytics in retail, ultimately enabling smarter, more customer-centric decision-making.

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