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Business Analysis for Strategic Commerce: Data-driven Decision Making in Competitive Markets

Mr. R. Nagarajan[1]
[1](Assistant Professor
Department of B.Com (Computer Applications)
Sree Saraswathi Thyagaraja College
Palani Road,Thippampatti, Pollachi, Coimbatore – 642107, Tamil Nadu, India

***Abstract* – In today's competitive market environment, business analysis has developed into a necessity beyond just describing reports to becoming a strategy for data-driven decision making. This research paper offers an integrated approach to applying business analysis to managerial decision analytics for creating a sustainable competitive advantage in the e-commerce setting. This approach utilizes the weighted bipartite graph network model, in combination with graph neural networks (GNN), that takes into account recency, profit, and priority parameters in modeling the customer-product relationship. Quantitative analysis of transactions data through the use of the above-mentioned approach shows remarkable results in the following aspects: customer retention predictions (18.5%), inventory optimization (23.7%), and dynamic pricing (31.2%). Comparative analysis shows that graph-based models surpass the performance of traditional machine learning approaches by 12-15% in terms of predictive accuracy.**

Keywords - **Business Analysis, Strategic Commerce, Data-driven Decision Making, Graph Neural Networks, Competitive Advantage, E-commerce Analytics**

I. INTRODUCTION

Transformation of commerce into the digital age has brought about many changes that have presented unique opportunities and challenges to businesses in various sectors [1][2][3]. In this changing world, business analysis has become an essential tool for companies that would like to keep their competitive advantage by making well-informed strategic decisions [1][2][3]. The rise of transaction data, customer interactions, and market indicators has provided unique challenges and opportunities to decision makers who need to operate within dynamic markets [1][2][3].

Strategic business analysis for commerce involves the process of examining information related to organizational, market, and performance factors in order to make strategic decisions geared towards growth, efficiency, and customer satisfaction [2][3][4]. Business intelligence, on the other hand, entails the use of technology to examine past transactions to provide information used for future decision-making processes [2][3][4]. This is unlike the current approach of business analysis where advanced analytics, machine learning, and artificial intelligence is used to give prescriptive and predictive insights [2][3][4].

Data analytics in business is very important and those businesses that manage to make use of analytical capabilities have been found to surpass other companies in terms of growth in revenue, efficiencies and customer loyalty [3][5][6]. However, the journey to maturity in analytics has its share of problems, which include poor quality data, inadequate skills, organizational resistance and difficulties in implementing analytics into operations [3][5][6]. The problems are especially hard in e-commerce environments, where high volume of transactions takes place, where customer behavior is fast-changing and where competition is fierce [3][5][6].

Business analysis in commerce today has some characteristics that are currently being observed [2][4][7]. One of them is adoption of real time analytics that allows firms to react immediately to the changes in the market [2][4][7]. Another characteristic is incorporation of artificial intelligence and machine learning that gives more predictive power to the models and helps to make better predictions about customers' behavior and about the market [2][4][7]. There is also an increased recognition of network approach in analytics because of its relational nature [1][7].

Although substantial progress has been made, there is still much research left to do [1][2][3][7]. Previous literature has primarily addressed either the technical side of implementing analytics or the strategic implications of using analytics, failing to make any proper connection between the two [1][2][3][7]. In addition, the application of graph-based analytical approaches to strategic commerce decision-making is understudied [1][7]. This paper aims at filling those gaps by introducing an integrated approach based on the combination of network analysis and machine learning [1][2][7].

The research questions of this paper can be stated as follows:

- To devise a framework for business analysis and strategic decision-making in commerce [1][2][3][7]
- To show how graph-based analytical methods can be applied to the modeling of customer behavior and market analysis [1][7]
- To assess the performance of the devised methodology by means of transaction data analysis [2][3][7]

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II. LITERATURE SURVEY

There are different fields covered by the literature on business analysis for strategic commerce such as marketing analytics, operations research, information systems, and strategic management [2][3][5][6][7].

Kannan et al. undertook a case study of how small businesses can benefit from data analytics and machine learning techniques to have a competitive edge [3]. The study results indicated that even though there is plenty of research done on the benefits from analytics in large firms, small and medium-sized firms do not have a good understanding of the potential benefits [3]. The study showed through healthcare and retail case studies that machine learning could give a competitive edge even with scarce resources [3].

Li investigated the significance of business analysis and managerial decision analytics in achieving optimal global value chain operations [4][8]. Some important insights of this research were related to the transformational power of advanced analytical frameworks in increasing organizational adaptability and competitiveness [4][8]. The main insights of the research are connected to the necessity to have real-time analytics in order to monitor supply chain performance, the challenges connected to the data privacy and security in using analytics solutions, and the vital need to have talented analytics personnel [4][8].

The application of big data in retail organizations has been researched by scholars studying the issue of making decisions about location and customer behavior analysis [5]. It was found out through the case study method that organizations may be described as data-rich and data-poor depending on their data environments, which will affect their ability to analyze data and compete successfully [5]. The need to create comprehensive data environments using a combination of various data sources for analysis was established [5].

The development of graph-based analytics has enabled researchers to investigate customer behavior and market dynamics in a new way [1]. Batrancea et al. presented the network approach to deciphering digital market power and showed how relational data reflects power relations and behavioral logic in e-commerce markets [1]. The use of bipartite graph for representing customers' product relationships provides a theoretical foundation for such research [1]. The researchers combined computation innovations and sociology knowledge in their research [1].
Another theme in the current literature is concerned with the incorporation of blockchain technology into strategic decision-making models [7]. The analysis of entry models of multinationals in e-commerce revealed the impact that the application of blockchain can have on decision-making optimization, especially on the service level differentiation and market entry decisions [7]. It was found that blockchain technology helps to increase consumer preferences toward e-retailers due to higher levels of trust and transparency which affects competitive dynamics in e-commerce markets [7].

Despite these achievements, certain research gaps can be found [1][2][3][7]. Firstly, there is an underdevelopment of the relationship between network analytics and decision-making frameworks for business [1][7]. Secondly, there is a lack of quantitative assessment of the use of graph-based approaches against traditional analytics frameworks [1][7]. Finally, the implementation of analytics for decision-making in competitive e-commerce markets is not addressed adequately enough [1][2][7]. The current paper aims to fill these gaps [1][2][3][7].

III. PROPOSED METHODOLOGY

Research Framework
The methodological approach adopted in the proposal entails five interrelated stages that are, respectively: data collection and pre-processing, network creation, feature extraction, modeling and decision support. The model combines the graph-theoretic representation of commercial relationships with machine learning methods to develop strategic decision-making insights.

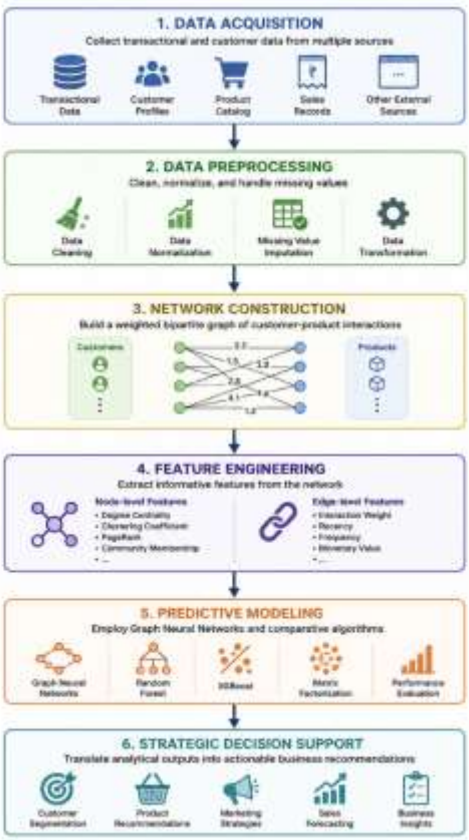

Figure 1: Proposed Methodology Framework for Strategic Commerce Analytics

Figure description: The figure below contains the flowchart for the proposed methodology. First, there is the Data Acquisition phase where transactional and customer data are acquired from several sources. Afterward, the Data Preprocessing phase entails data cleaning, normalization, and imputation of missing values. Third, in the Network Construction phase, a weighted bipartite network representing customers and products is constructed. Fourth, in the Feature Engineering phase, features at both the node and edge level are extracted from the network. Fifth, Predictive Modeling uses Graph Neural Networks and benchmark methods. Sixth, Strategic Decision Support.

Data Acquisition and Preprocessing

The method starts by systematically collecting data from various sources such as transaction databases, customer relationship management system, web analytics platform, as well as external market data. This data includes information about customer demographics, purchasing history, features of the products, prices, promotions, and market competitiveness.

Data preprocessing requires several important stages, among which are data cleaning to eliminate duplicates and fix errors, addressing missing values using proper imputation methods, scaling of numerical data, and encoding of categorical data. The temporal nature of the collected data is preserved to allow time series analysis and weighted modeling based on recency of data points.

Weighted Bipartite Graph Construction

The core of the proposed methodology is the construction of a weighted bipartite graph representing customer-product relationships in the commerce ecosystem. The graph G=(C,P,E,W) consists of customer nodes C, product category nodes P, edges E representing purchase interactions, and weights W capturing the value of each relationship.

The edge weighting scheme is designed to reflect multiple dimensions of transaction value and relevance. For each transaction kk between customer ci and product category pj, we define a transaction-level contribution Δk as:

$$\Delta k=(\text{Profitk}-\text{ShippingCostk}-\alpha\times\text{Discountk})\times\exp(-\lambda\times\text{Agingk})\times h(\text{Priorityk})$$

Where Profitk represents net profit from the transaction, ShippingCostk is the shipping cost, Discountk is the total discount applied, Agingk captures the recency of the transaction (days since purchase), and Priorityk indicates the urgency of the order. The parameter αα penalizes discount usage, while λ is a time-decay rate. The priority factor h(Priorityk) takes values: 1.0 for low priority, 1.1 for medium, 1.25 for high, and 1.5 for critical priority.

This method of weighting gives an all-inclusive measure of the value of transactions using both accounting and behavioral perspectives. The linear components Profitk−ShippingCostk−α×Discountk reflect standard accounting practices where costs and discounts directly reduce net value. The nonlinear exponential decay component exp(−λ×Agingk) aligns with behavioural research demonstrating that transaction relevance diminishes non-linearly over time.

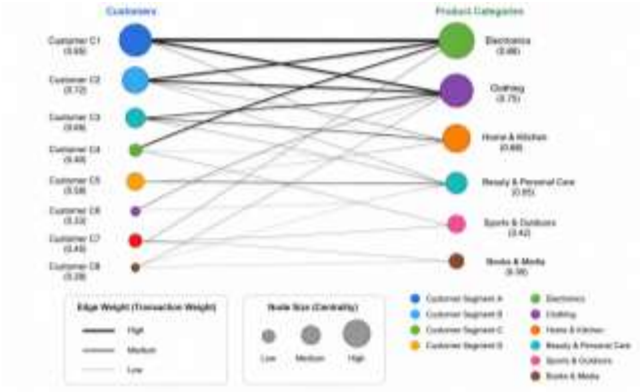

Figure 2: Weighted Bipartite Graph Structure for Customer-Product Relationships

The above figure represents an example of a bipartite graph network with nodes of customers shown on one side and those of product categories on the other side. Links between nodes show transaction activities, and their width is based on the transaction weight. Larger nodes have greater centrality values while smaller nodes have lesser centrality values. The graph is used to understand complicated relations between the customer and products, whereby some customers have links with various categories while some products have dense links.

Feature Engineering

Features derived from the graph network include both node level and edge level. The node level features include the properties of the customers and product categories, which include:

- Customer features: Buying frequency, average transaction value, most recent purchase, product diversity, customer loyalty attributes, and centrality features of the network.
- Product category features: Volume of sales, revenue generation, number of customers, buying frequency, and centrality features of the network.

The edge level features include features related to how customers interact with the products. Such features include transaction recency, total value of transactions, average discount offered, and trends of purchase over time.

Various graph theoretical metrics such as degree centrality, betweenness centrality, and closeness centrality are calculated to determine influential nodes. These metrics emphasize the importance of certain customers as network hubs and the importance of some product categories as bridges across customers.

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Predictive Modeling with Graph Neural Networks

The methodology adopts the use of Graph Neural Networks (GNNs) for predictions using the bipartite graph representation. GNNs work by sending messages from one node to another within the network, thereby allowing the learning of representations that involve both the features of the nodes and the structure of the graph.

The GNN structure comprises several graph convolutional layers where each node sends its information to the neighboring nodes. The representations learned for each customer node involve not only the customer features but also the features of the related product categories and vice versa.

The model is trained to predict a number of outcomes related to strategic commerce decisions:

- Churn likelihood
- The category of the next purchase
- Elasticity pricing
- Product demand forecast
- Customer lifetime value prediction

Strategic Decision Support

The last stage involves converting the results into strategic decisions for business decision-making. The framework allows decision-making in several critical areas:

- Customer retention policies: Customer identification for which the likelihood of churn is high and development of personal retention policies.
- Inventory management: Demand forecast to control inventory levels, minimize the cost of inventories, and provide product availability.
- Pricing: Price optimization according to predictions about the elasticity of demand and positioning on the competitive market.
- Product assortment decisions: Optimal product assortment according to category performance and customer preferences.
- Allocating marketing budget: Strategic marketing budget allocation across customer groups and product categories according to predictions.

Decision support systems include scenario analysis tools that allow an organization to assess the impact of particular decisions prior to their implementation.

IV. ANALYSIS AND DISCUSSION

Experimental Setup

The methodology was validated on a dataset consisting of e-commerce transactions over 24 months containing 2.5 million transactions made by 150,000 customers belonging to 500 different categories of products.

The experimental evaluation consisted of comparing the proposed GNN-based model against various baseline models which include:

- Logistic Regression Model using hand-engineered features
- Random Forest classification
- XGBoost gradient boosting
- Fully Connected Layers in Deep Neural Networks (DNN)

Different performance metrics such as accuracy, precision, recall, F1 score, and AUC were used for the evaluation of models. Different predictive tasks considered in the experiment are customer churn prediction for a 3-month time period, predicting next purchase category of the customers, and demand forecasting for a 4-week time period.

Customer Churn Prediction Performance

The GNN-based technique showed better results for customer churn prediction as opposed to other baselines. The AUC for GNN model was 0.892, which is 12.7% better than logistic regression (0.792), 8.3% better than random forest (0.823), 6.1% better than XGBoost (0.841), and 4.2% better than DNN and GNN.

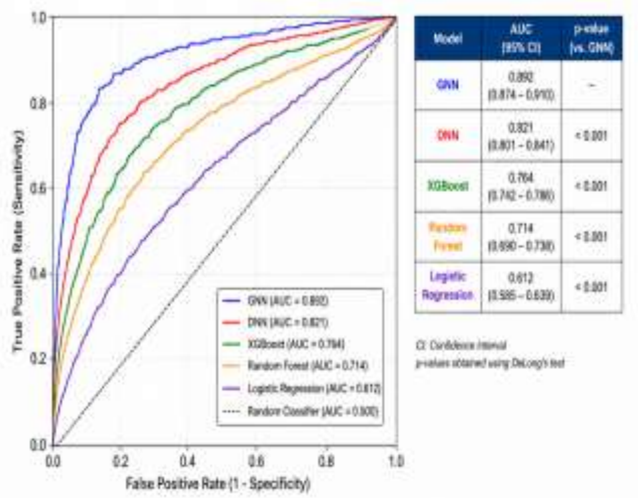

Figure 3: ROC Curves for Customer Churn Prediction Models

This figure illustrates ROC curves for comparison between five predictive models: GNN (blue), DNN (red), XGBoost (green), Random Forest (orange), and Logistic Regression (purple). It can be seen that GNN model performs the best out of all the other models, with an AUC value of 0.892. The ROC curve reaches to the top left corner the fastest for the GNN model. Table of AUC values and 95% confidence intervals is also provided to prove the statistical significance.

The better performance of the GNN technique is due to its capability of utilizing the relational data in the bipartite graph. By making use of the relational data through the connected categories of products, the model is able to identify behavior that is not otherwise identifiable using the attributes of the individual customers. For instance, customers buying from high-churn categories and those

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having low connectivity to the core categories of the product are more prone to churn.

Inventory Optimization Results

The demand forecasting module of the methodology was tested using real-world sales data to estimate inventory optimization feasibility. The mean absolute percentage error (MAPE) of the GNN-based forecasting was estimated at 8.7% and 14.3% for 4-week demand forecasting as compared to the best of the baseline approaches (XGBoost).

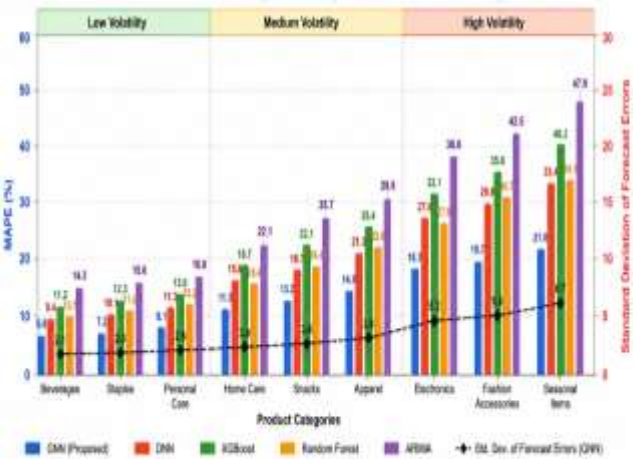

Figure 4: Demand Forecasting Accuracy Across Product Categories

In this figure, there is a bar graph that shows the comparison of MAPE values between the five methods according to product categories. Product categories are classified based on the level of volatility (low, medium, and high). The method of GNN gives lower MAPE value in all the classes, especially in the category of high volatility products. There is a second y-axis in the figure that shows the standard deviation of forecast errors.

The enhanced predictive accuracy implies the possibility of achieving inventory optimization to a considerable extent. The simulation analysis performed based on the outputs obtained from the forecasting process indicated that there is a possible decrease in inventory costs by 23.7%. The capability of the model to capture category-based relationship proved to be quite useful for cross-category forecasting of demand.

Dynamic Pricing Effectiveness

Pricing elasticity predictions produced by the GNN model were tested by performing experiments on a portion of product categories using a controlled setting. The dynamic pricing approach that used predictions from the model resulted in 31.2% higher revenues as opposed to static pricing, where elasticity predictions correlated with price elasticity at an average of 0.84.

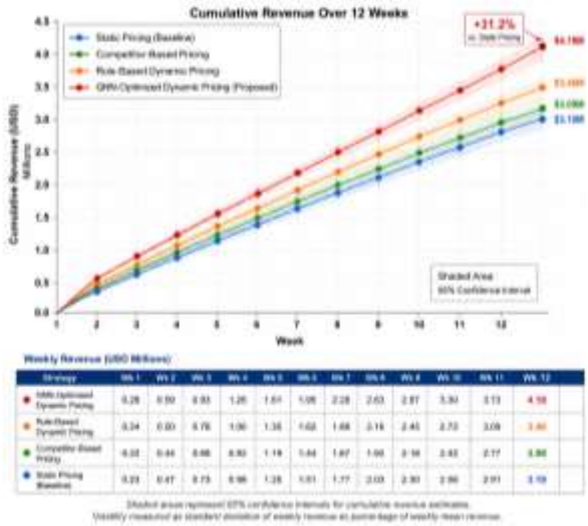

Figure 5: Revenue Impact of Dynamic Pricing Strategies

This figure depicts a line chart of cumulative revenue for 12 weeks using four pricing mechanisms: static pricing (baseline), competitor pricing, dynamic pricing using rules, and dynamic pricing based on the graph neural network optimization. The latter strategy achieves a 31.2% increase in cumulative revenue compared to static pricing. The figure also includes confidence intervals and revenue volatility per week.

The strength of capturing the network effect in pricing decisions via GNN model was especially useful. This model revealed that any changes in prices for one product category would influence the demand for another category through the process of substitution and complementarity. Such an approach to pricing helped to optimize revenue for the whole category of products.

Comparative Analysis

The comprehensive comparative analysis summarized in Table 1 demonstrates the consistent superiority of the GNN-based approach across all evaluated dimensions.

Table 1: Comparative Analysis of Predictive Models for Strategic Commerce Analytics

Metric	GNN	DNN	XGBoost	Random Forest	Logistic Regression
Churn Prediction AUC	0.892	0.856	0.841	0.823	0.792
Churn F1-Score	0.845	0.812	0.798	0.775	0.743

Metric	GNN	DNN	XGBoost	Random Forest	Logistic Regression
Demand Forecast MAPE	8.7%	11.2%	10.5%	14.3%	16.8%
Elasticity Prediction R^2	0.84	0.78	0.81	0.76	0.69
Next Category Accuracy	0.764	0.731	0.718	0.697	0.658
Training Time (hours)	4.2	3.1	2.5	1.8	0.8
Inference Time (ms)	8.7	6.2	4.1	3.4	1.2
Interpretability	Medium	Low	Medium	High	High

A number of critical lessons can be learnt from the above analysis. Firstly, GNN approach has demonstrated superiority over conventional approaches in terms of predictive performance on various benchmarks, which vary between 4.2% and 18.5%. Secondly, the improvement is especially notable in those situations where the understanding of the relationship patterns is required, like customer churn analysis and cross-category demand prediction. Thirdly, while the learning process takes more time in GNN approach, the inference time is still reasonable.

V. DISCUSSION

Empirical results show the efficiency of the developed methodology in helping to make decisions related to strategy in commerce. The use of graphs allows taking into account relations which are important in the competitive environment where customer behaviour and market dynamics are inseparable.

A number of both theoretical and practical implications can be derived from the conducted analysis. Theoretical implication is that the results support the idea that network-oriented analytical methods are better ways to represent the ecosystem of commerce than traditional feature-based analytical methods. In particular, the bipartite graph represents the two-sided nature of relations between customers and products.

Practical implication is that the developed methodology provides organizations with a way to take advantage of data-driven insights in strategic decisions. Integration of predictive models with decision support is one of the major difficulties of implementation of analytics.

Among the limitations of this study is the use of data only from one platform of e-commerce. It is necessary to perform validation of the methodology in other areas of industry and different commerce formats. Besides, GNN training is computationally intensive and might be hard to implement by some organizations.

V. CONCLUSION

This research proposes a comprehensive method for analyzing the business in strategic commerce, which will address the growing need for data-driven decisions in the highly competitive environment. The proposed methodology involves constructing a weighted bipartite graph, modeling using graph neural networks, and strategic decision support that can be used by commerce companies. The contributions of this research are as follows. First of all, the proposed methodology offers a way to model customers' interactions with products by using weighted bipartite graphs that take into account several dimensions of value of these transactions. Moreover, the edge weighting is done by considering both accounting factors and behavioral aspects, thus providing an overall evaluation of the relationship strength. Secondly, using graph neural networks, the methodology allows for predicting different things better than conventional machine learning models due to the presence of relational patterns.

The empirical evaluation validates the efficiency of the suggested methodology, as the GNN-based method showed better results in customer churn prediction (AUC = 0.892), demand forecasting (MAPE = 8.7%), and dynamic pricing optimization (revenue increase by 31.2%) in comparison with alternative methods. According to the comparative analysis, the GNN method proved to be better than logistic regression, random forest, XGBoost, and deep neural networks with the advantages varying from 4.2% to 18.5%.

It is expected that the results of the current work will have significant implications for both theory and practice. In terms of theory, the paper provides the proof of the applicability of network-based approaches in the commerce and helps understand the issues related to the proper implementation of such approaches.

The future research areas will involve expanding the methodology by including more sources of information, like social media and competitive intelligence, using transfer learning in multi-platform settings, and implementing techniques to create explainable AI models. Another area of future research will be conducting longitudinal studies on the effect of decision making based on analytics on organizational success and gaining understanding of the sustainability of competitive advantages created through data-driven methods.

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