

Article

Integrating Generative AI into Business Analytics for Automated Strategic Insights

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Abstract: The rapid advancement of Artificial Intelligence (AI) has transformed traditional business analytics into a descriptive reporting apparatus into predictive intelligence systems. There is a major disparity between the predictive analytical output and the strategic action taken. This study proposes a combined approach of Generative Artificial Intelligence (GenAI) and advanced business analytics to facilitate strategic insight creation with the help of automatic means. The study uses the dataset of Instacart Market Basket Analysis that has over three million actual grocery transactions to develop a predictive classification model of whether a product will be reordered in case of past customer purchase history. Machine learning techniques are employed to analyze repeat buying behavior, shopping cart sequences and product-product affinity in retail transactions. In addition to predictive modeling, this study also presents a Generative AI layer that is meant to analyze the output of the analytics and provide automatic executive-level strategic recommendations in retail decision-making. The system converts predictive results into context business suggestions including inventory optimization plans, customized promotional campaigns, and cross-selling suggestions instead of providing numerical probabilities on their own. This approach represents a transition from traditional decision-support systems to autonomous strategic intelligence systems. The proposed framework is measured based on predictive performance measures such as F1-score and ROC-AUC, and qualitative measures of strategic relevance and managerial interpretability. The results suggest that the application of Generative AI to business analytics brings a high level of efficiency to decision-making, less managerial cognitive load, and better applicability of the analytical results in practice. This study contributes to the emerging field of AI-enhanced business analytics as it offers a scalable framework connecting predictive modeling and strategic reasoning. This study also has theoretical and managerial implications for retail organizations that are interested in using Generative AI to create intelligent and automated decision ecosystems.

Keywords: Generative Artificial Intelligence (GenAI), Business Analytics, Automated Strategic Insights, Market Basket Analysis, Retail Data Analytics and Predictive Modeling.

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Introduction

A. Background

The accelerating shift to digitization of business operations has had far reaching impacts on the way organizations have been functioning, competing and generating value. In all sectors, especially in the retail business, digital platforms are producing enormous amounts of transactional data that record the behavior of the customer, buying behavior, and operational processes in real time [1]. This information overload has reinforced the use of business analytics as a strategic asset by allowing companies to derive actionable

insights that can be used to drive efficiency, better inventory management, personalized marketing campaigns, and retention of customers. Descriptive, diagnostic and predictive methods of business analytics are major concerns of traditional business analytics systems. These are systems that use statistical models and machine learning algorithms to classify trends, predict demand and estimate customer purchasing tendencies. Although these developments have been made, predictive results are usually presented in quantitative form in the form of probabilities, classification labels or performance measures. The outputs have to be interpreted by managers to yield significant strategic implications, which creates delays, cognitive burden and possible biases in the decision-making process. With the competition among retail organizations increasing, organizations need quicker and smarter systems that can not only forecast results but also automatically interpret the results of the analysis into action plans. Recent developments in Generative Artificial Intelligence (GenAI) provide potentially helpful abilities to fill this gap. GenAI systems are also able to comprehend contextual data, achieve natural language explanations and even create recommendation stories, unlike traditional predictive models [2]. The use of Generative AI in business analytics pipelines is a paradigm shift of business decision support systems to autonomous strategic intelligence systems. The retail sector: especially the Instacart Market Basket Analysis dataset of large-scale transactional environments, offers a very good empirical environment in which to study how predictive modeling and generative interpretation can be integrated to generate strategic insight on-the-fly.

B. Development of Business Analytics to Intelligent Decision Systems

Business analytics has significantly developed in the last 20 years to develop beyond primitive reporting systems to sophisticated predictive and prescriptive systems. Firstly, the organizations used descriptive analytics to generalize previous data and produce periodical reports [3]. With the growth of the computational capacity, predictive analytics came into existence, which permitted companies to anticipate customer movements, project demand, and detect patterns of risk as a part of machine learning algorithms. More recently, prescriptive analytics presented optimization methods to suggest possible courses of action on the basis of anticipated results. Even prescriptive systems rely on structured logic based on rules and pre-defined decision parameters. They are not able to have the contextual thinking and flexible communication skills that are needed in the executive level strategic decision-making. This has posed a limit on the development of emerging demand to intelligent decision systems with predictive modeling and cognitive interpretation. The next step in this development is generative AI technologies, and especially large language models. These systems can combine analytical results, situational business intelligence and business goals to produce coherent, human readable strategic judgments. The shift to intelligent decision systems, as opposed to predictive models, is a wider shift to a digital strategy [4]. Companies are starting to regard AI as an additional conservative device, rather than just a prediction instrument, but as a partner that can enhance managerial cognition. Combining Generative AI with predictive analytics may be used to generate reports automatically and make decisions responsive to changes in retail settings with dynamic customer behavior and volume of transactions. This development is a pivot to AI-driven strategic intelligence as opposed to data-driven analytics.

C. Generative AI in Retail Analytics

The retail sector is one of the few industries that can take advantage of the adoption of Generative AI in business analytics because of its data-driven and customer-oriented nature. Grocery retail platforms raise incessant flows of transaction information, which indicate precise customer preference, re-ordering propensity, product affinity, and buy frequency. The predictive models can be useful in estimating the reorder probabilities effectively finding patterns of associations between products [5]. The numerical results of these are not usually strategically interpreted. Generative AI is the introduction of the ability to fill this interpretive gap. Generative AI systems have the ability to generate

strategic narratives to help managers make decisions by examining the model outputs as feature importance, reorder likelihood, and pattern of basket composition. As an example, rather than just notifying of high reorder rates of certain types of products, an AI-enhanced system will be able to suggest specific promotion services, dynamic inventory management, or targeted marketing programs. Furthermore, Generative AI enables strategic reporting to be expanded with respect to scale. Conventional methods of reporting business involve manual making of executive summaries and insight documents [7]. Automated insight generation saves on time to make decisions and enables the managers to stick to strategic planning as opposed to interpreting data. Generating real time strategic insight is of great competitive advantage in the retail markets that are highly competitive and where consumer preferences are changing very fast [7]. Consequently, integrating predictive analytics with Generative AI would result in an overall retail intelligence platform that would be able to provide automated and context-driven strategic recommendations.

D. Problem Statement

Even though machine learning models are often useful in predicting customer purchasing behavior, they are usually expressed as numerical probabilities, classification, or statistical measures. These outputs do not necessarily present strategic advice or a situational explanation of what the manager should do [8]. The consequence of this is that decision-makers have to interpret predictive results by hand, which adds to cognitive load, decreases response time, and creates the risk of bias [9]. This is the lack of connection between predictive analytics and actionable strategy which curbs the practical utility of advanced analytics systems [10]. Thus, the necessity to implement a unified system, which would utilize Generative Artificial Intelligence to convert predictive results into automated and contextual strategic insights in retail business settings is critical.

E. Objectives of the Study

In this study, we intend to create and test a Generative AI-enhanced business analytics system that will be used to generate automated strategic insights in retail societies [11]. The specific objectives are:

- To create a predictive classification model of reorder behavior in groceries based on transaction data.
- To add a Generative AI layer, which can understand analytical outputs.
- To computerize the production of executive-level strategic recommendations.
- To determine how well AI-generated insights can be used to enhance the efficiency and interpretability of decisions.

F. Research Questions

The research questions that are to be answered by the study include:

1. What is the best method to incorporate Generative AI in business analytics systems to convert predictive outputs into strategic decisions?
2. Does predictive retail analytics become more interpretable and useful when integrated with Generative AI?
3. Is automated strategic insight generation applicable in enhancing effectual decision-making within the retail business context?
4. What managerial implications do the use of AI-augmented analytics systems have?

G. Significance of Study

This study has theoretical and practical implications to the new realm of AI-enhanced business analytics [12]. Theoretically, it contributes to the current knowledge of the decision support systems field by suggesting a framework that combines predictive modelling with Generative AI-based interpretation. Although previous study has paid much attention to enhancing predictive accuracy, there is little literature on automating

strategic reasoning processes. This gap is filled by the study, which expands the conceptual knowledge of the transformation of Artificial Intelligence into the strategic intelligence systems as opposed to its status as an instrument of analysis. Practically, the study can be of great use to retail organizations aiming at improving efficiency and competitiveness of decisions made [13]. Computer-based strategic insights creation decreases the usage of human-followed interpretation, speeds up the response rate, and makes the analytic output more understandable. The retail managers will be able to utilize AI-generated suggestions concerning inventory optimization, strategies for retaining the customers, and targeted marketing efforts. The framework enhances scalability in reporting workflows; therefore, organizations can handle big transactional data. This study also gives implementation strategy recommendations to AI, by showing how Generative AI may be incorporated into the current analytics platforms. Due to the growing number of organizations that use AI technologies, it is necessary to learn how they integrate them [14]. This study will enable the creation of smart, adjustable and expandable decision ecosystems that lead to the improvement of strategic agility long-term business performance.

Literature Review

A. Business Analytics of Retail Decision-Making

The intensive development of online transactions and high volumes of consumer data has made business analytics an essential aspect of contemporary management of retail organizations [15]. Companies in the retail sector are progressively using data-driven insights to gain a better insight into customer behavior, inventory optimization, supply chain optimization, and overall performance of operations. Business analytics usually entails three major steps which include descriptive analytics, predictive analytics and prescriptive analytics. Descriptive analytics is aimed at generalization of past data to show the tendencies and patterns in consumer buying behavior. Descriptive analysis in the retail store setting is frequently used to analyze the records of transactions, customer demographics, and category performance in order to learn about the past [16]. Predictive analytics is an extension of this, using statistical models and machine learning algorithms in order to predict future consumer behavior. In retail, predictive models are very common to predict customer demand, predict whether to reorder a product or not, and suggest a product based on its earlier purchase history. Even with their predictive abilities, a lot of analytics systems still need human interpretation to understand the model outputs and take relevant managerial decisions. This has led to the dilemma of decision-makers harnessing analytical results into strategic formulations in a rapid manner. The growing sophistication of retail data has compounded the problem of requiring sophisticated analytics models that are capable of processing high volumes of data effectively [17]. The introduction of modern data infrastructures and machine learning algorithms led to the enhancement of the capacity of organizations to analyze high-dimensional retail data. The business analytics frameworks are still highly concentrated on quantitative outputs and statistical sense-making as opposed to automated strategic insight generation. This drawback underscores the necessity of novel analytics methods that would integrate predictive modeling with smart interpretation mechanisms that could generate viable recommendations to decision-makers.

B. Customer Behavior Prediction using Machine Learning

The machine learning models have greatly revolutionized the capability of the organization to analyze the complex data and reveal the hidden behavioral patterns in the purchasing data of consumers [18]. Machine learning models have been extensively used in retail analytics to forecast customer preferences, purchase frequency, product demand and reorder behavior. These models extract patterns based on the previous transactions and apply patterns in prediction of future consumer activities. The classification

algorithms will come in handy especially when it comes to predicting customer reordering of certain products during the subsequent shopping sessions [19]. Decision trees, support machines, logistic regression, and ensemble learning techniques that are commonly applied when predicting behavior of customers. These models are based on various characteristics obtained out of the transactional data, such as frequency of purchase, time between purchases, product line, position on the cart, and purchasing patterns. Machine learning models can detect such patterns that would not be easily seen as a result of traditional statistical analysis using these behavioral indicators. The other significant benefit of machine learning in retail analytics is that it can process bulky and high-dimensional data [20]. Retail data are usually in millions of transactions and thousands of product lines and therefore, the standard analytical methods are less applicable. Such data may be processed by machine learning algorithms and produce the correct predictive outcomes. But the interpretation of machine learning systems is one of the greatest constraints. Predictive outputs are often in the form of probability scores or category labels, and these do not necessarily imply action steps that can be taken by managers [21]. Therefore, despite the accuracy of the machine learning models in predicting consumer behavior, the discrepancy between predictive outcomes and strategic decisions is a major issue of business analytics research.

C. Generative Artificial Intelligence is used in Strategic Insight Generation

The developments in artificial intelligence have seen the introduction of Generative Artificial Intelligence as an effective approach to making analytical results more interpretable and usable [22]. The generative AI systems can generate human-like text, explanations and recommendations based on structured and unstructured data inputs. Generative AI can be used in the context of business analytics to change the conventional analytical systems by generating meaningful strategic narratives out of the outputs of the numerical models [23]. This information is especially useful in retail settings where decision-makers need to make quick analytical decisions based upon the available results. Generative AI may process predictor model results, forecast the core trends and produce suggestions regarding stock upkeep and positioning, advertisement initiatives, and business attitude tactics. Organizations can greatly ease the cognitive load of analysis by automating the interpretation of analytical results of large quantities of data. Explainable analytics Generative AI systems may be additionally used to support explainable analytics to qualify transparency and trust in automated decision-support systems by giving the model predictions in natural language [24]. The combination of Generative AI with predictive analytics thus forms a good future direction of business intelligence systems. Organizations can use AI-generated insights to enable more natural and practical decision-making operations as opposed to using statistical dashboards and technical reports. With the volume of transactional data produced by digital retail ecosystems steadily growing, the synergistic role of machine learning prediction and Generative AI interpretation might allow the creation of intelligent analytics systems that will be autonomous in generating strategic insights to managers and business leaders.

D. Existing Research and Research Gap

The article *Generative AI in Market Analysis in Business Consulting: Revolutionizing Data Insights and Competitive Intelligence* by Suprit Kumar Pattanayak is an important addition to the existing research body on artificial intelligence in business analytics. The paper examines the application of generative artificial intelligence in changing the conventional market analysis and competitive intelligence activities in business consulting settings. Traditional market analysis techniques are usually based on heavy manual data gathering, statistical analysis, and manually prepared reports, which could be time-consuming and even restrict the pace of strategic decisions. The paper brings out the fact that the generative AI facilitated by machine learning and natural language processing technologies have the potential to consume immense amounts of structured

and unstructured data and subsequently produce automatic analytic reports and strategy [1]. The ability enables organizations to detect market trends, predict future demand trends and get usable intelligence which would help them make superior business strategies. This study stresses that the analytical tools based on AI will allow conducting the analysis in real-time and making decisions quicker, enhancing the overall quality of work and competitiveness of the consulting companies. Although such benefits are present, the paper also points out some of the drawbacks of the adoption of generative AI technologies. The problems of data privacy, algorithm bias, and the necessity of technical specific knowledge are also troublesome to the organization that implements AI-based analytical systems. More to the point, the paper is predominantly conceptual instead of empirical evidence based on considerable transactional volumes of data on the issue of generative AI in market analysis. As a result, there is a gap in literature on how generative AI can interact with predictive analytics models to automatically convert the results of the analytics into strategic business insights. To fill the existing gap, the current research suggests a solution to the problem, in which machine learning-based predictive modeling is paired with a generative AI interpretation layer, to produce automated strategic recommendations in retail business analytics systems.

The article by Harish Kumar Sriram, entitled *Integrating Generative AI into Financial Reporting Systems to Provide Automated Insights and Decision Support*, is an important addition to the growing body of research on Generative Artificial Intelligence in decision-support systems. The study investigates the opportunities to introduce Generative AI technologies to the Financial Reporting System (FRS) to facilitate the process of interpreting corporate financial information and enhancing the process of strategic decision-making. The traditional financial reporting systems mainly produce structured financial reports and numerical measures including profitability, liquidity, and solvency measurements [2]. Irrespective of the fact that such reports present essential financial data, managers and financial analysts have to frequently interpret such numbers manually in order to obtain significant strategic information. What the study notes is that with the aid of deep learning methods, Generative AI can revolutionize financial reporting by automatically producing narrative explanations, analytical summaries and contextual insights based on complex financial data. This integration can provide a manager with concise and real-time information about corporate performance, organizational structure, and strategic financial decision making (capital budgeting and profit allocation) through advanced analytical capabilities that include the characteristics of a what-if scenario analysis that helps managers understand the possible consequences of alternative strategic and tactical decisions prior to implementation, the research proposes. This feature enhances decision efficiency by saving on the time taken to interpret financial data and also offering automatic replies to user queries on the performance of the organization. It is also suggested in the study that AI-based financial reporting systems have the potential to be centralized sources of analysis, which could be used to serve the corporate management, corporate regulatory authority, and financial authorities. Although the study has shown the usefulness of Generative AI in financial reporting and automated insights generation, it is more so on the context of financial analytics and lacks a comprehensive exploration of how Generative AI can be integrated with predictive analytics systems to automatically convert analytic results into strategic guide to action within the wider business analytics frameworks such as retail customer behavior analysis and market-driven decision-making.

In the article *Leveraging Data Mining and Generative AI to an advanced business intelligence in Cloud computing* by Nadir Ali, the author discusses the potential of combining data mining methods with Generative Artificial Intelligence to improve business intelligence capacity in a cloud computing setup. As noted in the research, cloud computing platforms have scalable and flexible infrastructures, which enable organizations to process and analyze large volumes of data with ease. With the integration

of cloud-based data mining methods and generative AI technologies, the businesses can derive greater information from complicated datasets and facilitate more accurate strategic decision-making. The paper highlights that generative AI builds upon the existing business intelligence tools by providing the possibility to create new analytical models, project future tendencies, and identify the hidden patterns that other analytical methods are unlikely to discover. Several important analytical steps, including data cleaning, feature selection, anomaly detection, and predictive modeling, can be automated by means of the introduction of AI-powered data mining systems and thus enhance the efficiency and accuracy of the analytical procedures. The study also points to the fact that generative AI can be used to create synthetic datasets to overcome the problem of data scarcity and enhance the predictive model performance. This process is also improved by cloud-based infrastructures that provide the ability to compute with great powers, process data faster, and analyze data in real time. Consequently, the organizations are able to produce almost instant information that can be used to streamline their operations, improve customer experience, and predict trends in the market. The study also mentions the possible challenges with this technical integration, such as data security issues, privacy protections, and regulatory compliance of cloud-based systems. Although the study shows the benefit of integrating generative AI and data mining and cloud computing in order to enhance business intelligence systems, it mainly concentrates on the infrastructure level and theoretical benefits of the research to empirical applications of the research in practical strategic insights of managerial decision-making based on real transactional data.

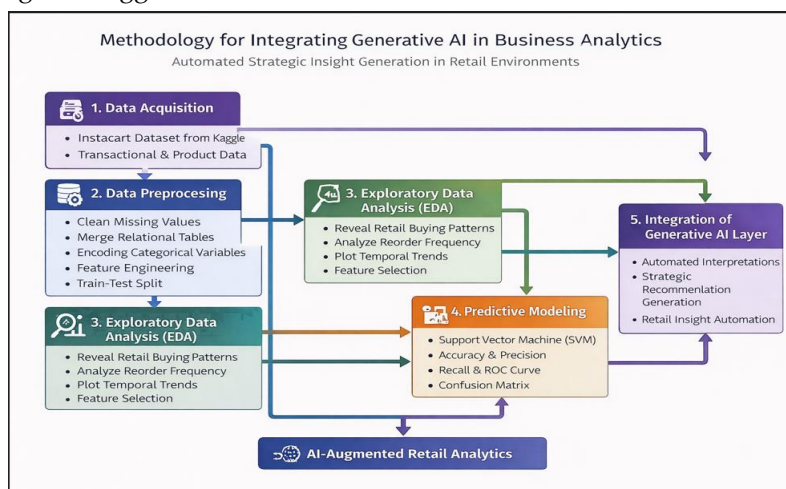
The article by Suprit Kumar Pattanayak, which is called *Leveraging Generative AI to Enhanced Market Analysis: A New Paradigm to Business Consulting*, discusses the increasing role of Generative Artificial Intelligence in enhancing the market analysis and strategic decision-making within the business consulting industry. The study points out that in most cases, traditional methods of market analysis rely on manual data gathering, traditional methods of analysis and few forecasting models that might be incapable of providing timely and precise information in fast moving market conditions. Generative AI represents a revolutionary solution as it allows handling data on a higher level, recognizes habits, and generates models automatically [4]. The study shows that market intelligence can be improved greatly through generative AI because it can analyze consumer behavior and identify new trends to assess the strategy of competitors more effectively than the traditional analytical approach. Generative AI systems can produce valuable insights that can guide consulting firms to enhance their forecasting effectiveness, efficiency, and customer satisfaction through machine learning algorithms and data analysis on a large scale. In addition, technology helps organizations in converting large amounts of diverse market data to actionable intelligence that aids decision-making. The research also mentions that there are a number of obstacles concerning the work with generative AI such as the problem of algorithmic prejudice, data security, and the necessity to possess a high technical level in order to operate AI-driven technologies. This study also concentrates more on the conceptual arguments and case observations instead of empirical execution of the study relying on extensive transactional data sources. Therefore, it is a research gap that remains to be filled with how generative AI may be combined with predictive machine learning models to automatically convert analytical results into strategic insights in data-driven business analytics settings. In this respect, to fill this gap, the current study suggests an integrated framework that integrates predictive analytics with a generative AI interpretation layer to produce automated recommendations on strategy in retail analytics.

The articles by Euromissile Francis Onotole, Tunde Ogunyankinnu, Yetunde Adeoye, Akintunde Akinyele Osunkanmibi, Godwin Aipoh, and Joseph Egbemhenghe, called *The Role of Generative AI in Developing New Supply Chain Strategies Future Trends and Innovations*, are dedicated to the transformative role of Generative Artificial Intelligence on the contemporary supply chain management and strategic planning. According to the research, the classic supply chain system is usually vulnerable to the

issues of demand turbulence, inefficiency in operations, lack of forecasting ability, and disturbance incurred as a result of international economic or political factors. Generative AI proposes a data-centered strategy that increases accountability of a supply chain through advanced predictive analytics, forecasting demand, and optimization of inventory. Generative AI systems can analyze big data sets of past and current information through machine learning algorithms like deep neural networks and natural language processing to produce predictive information that can be used to make preventive decisions. The paper also states that generative AI is able to simulate various supply chain conditions, enabling the organization to analyze possible risk factors and work out a contingency plan in case of supply disruptions [5]. The combination of generative AI with new technologies including Internet of Things (IoT) and block chain can help to increase the transparency of the supply chain, allow monitoring the operations in real-time, and facilitate sharing data between various supply networks with the help of secure methods. Such capabilities enable organizations to develop more responsive and agile supply chain strategies that respond to the changing market conditions. Although those strategic benefits of generative AI in supply chain innovation are highlighted, the research is primarily conceptual and technological in its views, not the implementation of the concept on the empirical basis of large-scale operational datasets. Therefore, there is still a research gap on how generative AI can be combined with predictive machine learning models in business analytics systems that automatically create actionable strategic insights on real transactional data. To fill this gap, the current study examines how generative AI could be integrated with predictive analytics models to generate automated strategic recommendations in the retail business analytics settings.

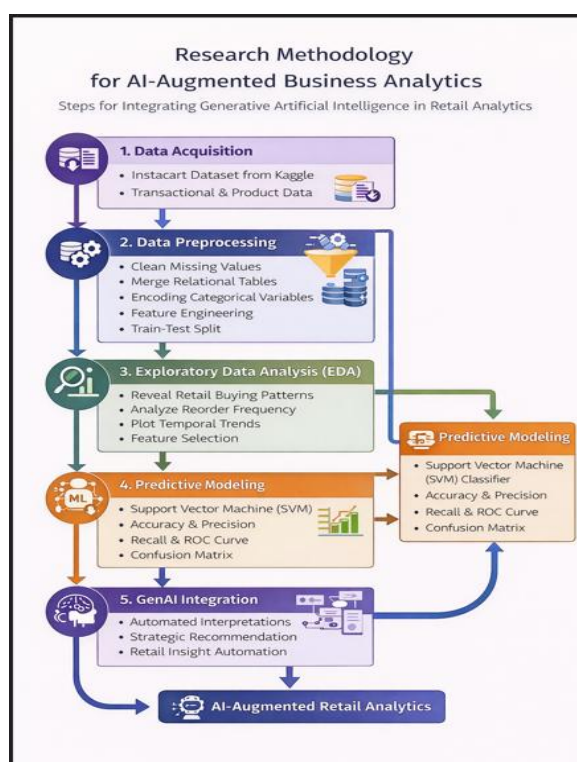
Methodology

This study adopts a quantitative, data-driven research design to explore the potential of Generative Artificial Intelligence (GenAI) to be incorporated into business analytics systems to generate strategic insights automatically [25]. The algorithm will adopt a five-step process, which includes data collection, preprocessing and exploratory data analysis, predictive modeling, and artificial intelligence interpretation. The retail transactional data is used to determine the behavioral patterns and foretell the reorder likelihood of products. A Support Vector Machine (SVM) model is made and assessed based on conventional performance indicators [26]. Lastly, a layer of Generative AI is conceptually developed into predictive outputs so that the analytical outputs are processed into automated, context-sensitive managerial suggestions.



This diagram presents a methodology workflow that combines predictive analytics and Generative AI to provide retail insights

The methodology diagram shows how the research was conducted in a systematic way to incorporate Generative Artificial Intelligence in business analytics to produce automated strategic insights in the business world in retail contexts [27]. The first step is Data Acquisition, during which the Instacart data is obtained on Kaggle, which contains transaction and product-level information. The second step, Data Preprocessing, is cleaning missing data, combining relational data, encoding nominal data, feature engineering and separate training and testing data. After preprocessing, an Exploratory Data Analysis (EDA) undertaking is taken where patterns in the retail purchasing behavior are to be found, reorder frequency analyzed and finding trends in buying patterns over time [28]. These observations are used to select the features in the predictive modeling. Predictive Modeling phase involves the application of the Support Vector Machine (SVM) algorithm to predict reorder behavior and also consider performance of the model in terms of accuracy, precision, recalls, ROC curve and confusion matrix. Lastly, Predictive Results are converted into automated interpretations and strategic suggestions to use in retail decision-making by the Generative AI Layer.



This flowchart illustrates the research methodology that combines predictive analytics and Generative AI

The flowchart shows the research design that will be used in the integration of Generative Artificial Intelligence in business analytics to create automated strategic insights in the retail setting [29]. It starts by first acquiring Data through Data Acquisition: The Instacart data will be obtained on Kaggle that will indicate transactional and product-related retail information. Then the Data Preprocessing stage; at this step, raw data is purged, missing values are processed, relational datasets are joined, categorical variables are coded, and feature engineering is applied. The data is further separated into the training and testing sets to facilitate sound model testing. The second step is Exploratory Data Analysis (EDA), which is performed to determine the trends in retail buying, reorder frequency, and the trends in the temporal distribution of purchasing among customers [30]. These lessons can be used to inform the process of feature selection. Predictive Modeling stage involves the use of Support Vector Machine (SVM) classifier to predict reorder behavior and model performance is measured based on accuracy, precision, recall,

ROC curve, and confusion matrix. Lastly, the implementation of Generative AI reshapes predictive outputs into an automated interpretation and strategy retailing.

A. Research Design

The research design of the study is quantitative and data-driven to examine the ways in which Generative Artificial Intelligence can be incorporated into the business analytics systems to produce automated strategic insights in the retail settings [31]. The research is based on the investigation of mass transactional information to find the trends in customer buying behavior and forecast the likelihood of reordering the product. It introduces a systematic analytical system comprising exploratory data analysis, machine learning-based predictive modeling, and AI-assisted interpretation of the results of the analytical systems. The research involves the use of secondary sources, i.e., a publicly available dataset on retail, which allows the researcher to investigate the actual consumer buying behavior. The design of the research is based on the predictive analytics methodology in which transaction history records are utilized to train a classification model that can predict reorder behavior [32]. The feature engineering methods are used to extract significant behavioral variables like frequency of purchasing, timing of order and product category relationship. In order to measure predictive effectiveness of the model, various statistical assessment measures are employed such as accuracy, precision, recall, F1-score, ROC curve and confusion matrix. Along with predictive modeling, the research design includes an idea of a Generative AI layer that interprets the results of the analytical work and converts them into a strategy offered to the decision-making process in retail [33]. This design in one allows the study to help fill the gap between the technical outputs of the analytics and the managerial implications.

B. Data Source and Description

The dataset used in this study is the Instacart Market Basket Analysis, which was received on Kaggle. The dataset has over three million grocery orders of over 200,000 users and gives a big transaction environment of retailer transactions that can be used in study regarding predictive analytics [34]. It has transactional data in detail that includes order ID, user ID, product ID, and order sequence number, order day of week, order hour and days since previous order. The data is represented in various relational files, such as orders.csv, order products prior.csv, order products train.csv, products.csv, aisles.csv and departments.csv. Orders file contains the order history in terms of time and user level, and the prior and train files give the product history in terms of transaction with reorders indicators [35]. Categorical classification of the product is provided by the products, aisles, and departments files. These relational data were linked together with such common keys as order-id and product-id to build a single analytical data. The dependent variable on predictive modeling is the reorder variable (binary 0 = No, 1 = Yes). The size and the heterogeneity of the dataset render it very suitable to study the pattern of customer behavior, demand forecasting, and AI-based retail decision systems [36]. The structure also facilitates descriptive and predictive analytics, which allows overall assessment of the business analytics performance.

C. Data Preprocessing

The preprocessing of the data was done to guarantee the analytical consistency, accuracy and model reliability [37]. To begin with, the cases of missing values in the days since prior order variables were addressed accordingly since first-time orders have a lot of null values. They were considered to be structurally missing, and not wrongly recorded data. Subsequently, primary and foreign keys were used to unite relational tables to create aggregated data on a product-order basis [38]. Numerical encoding was applied to categorical variables like department, aisle, and day of week so that they can be compatible with the machine learning algorithms. The engineering of features was conducted to make the prediction more accurate. Derived variables were the reorder frequency per user-product pair, average cart position, total previous purchases, order recency, and time-

based variables, including order hour and order day. The continuous features were normalized to ensure that the proportional influence is maintained during the training of SVM. It was then split into training and testing to assess the performance of generalization. This was divided into stratified groups that maintained the balance in the classes, as there might be an imbalance between the reorder and non-reorder classes [39]. These pre-processing operations had the effect of ensuring that the data are clean, organized, and optimized to predictive modeling. The study enhances the consistency of classification performance by converting raw transactional data into analytical meaningful features, which is useful in integrating with Generative AI to interpret strategic implications.

D. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed in order to identify the concealed patterns and trends in the retail data. Reorder distribution, product concentration in departments, cart position trends, and temporal buying patterns were analyzed by using descriptive statistics and visualization [40]. It was found that the percentage of reordered goods was high meaning that customers had a great deal of loyalty and they were habitual consumers. On the departmental level, the analysis revealed the focus on these categories, i.e. personal care, snacks, and pantry goods, which place the propositions of strategic product assortment structures [41]. The frequency analysis of the orders within the hours of the day proved the most active purchases occur in the mid-morning hours and early afternoon of the day, which is a lifestyle-based consumption pattern. Cart position analysis revealed that products that are reordered often have earlier positions on the cart sequence and hence habitual selection behavior is indicated. Regency effects also indicated that the less order time between orders, the higher the reorder probability. These descriptive revelations were used to guide features choice in predictive modelling. The variables that showed high behavioral impact were given a preference in the classification stage [42]. Besides enhancing the design of the model, EDA also delivered business intelligence information that is in line with strategic retail decision-making. This was taken in order to make predictive modeling based on empirical behavioral insights rather than algorithmic optimization.

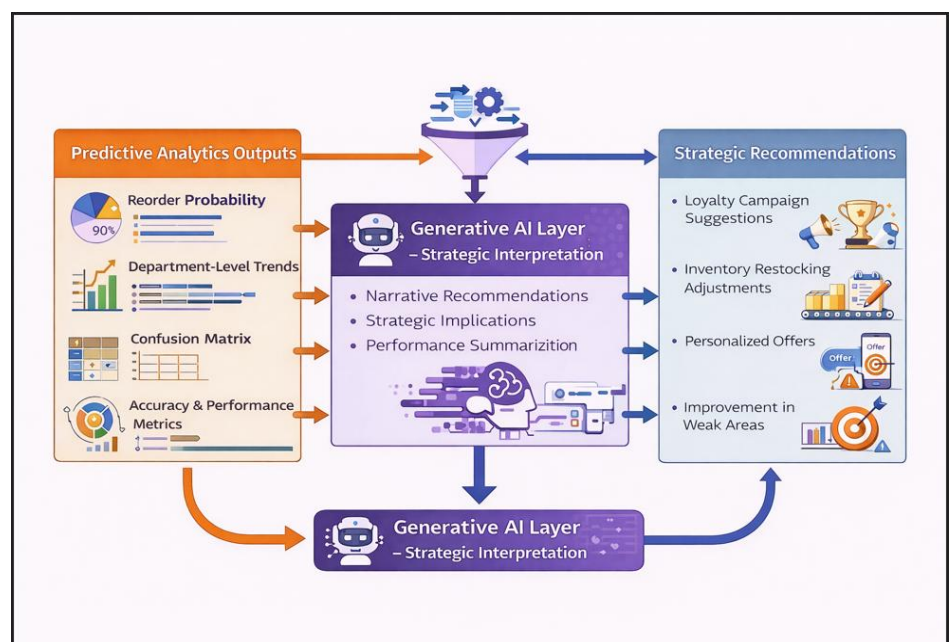
E. Predictive Modeling

Support Vector Machine (SVM) classifier was also used to forecast the possibility of a product being reordered. SVM had been chosen because it is robust in terms of working with high-dimensional data and capable of working with binary problems related to classification. Training of the model was done on engineered behavioral and transactional features as obtained in preprocessing [43]. The use of a linear kernel was done to guarantee computational efficiency due to the size of the dataset. Hyper parameters were set so as to strike a balance between model bias and variance. The model was fitted using the training dataset and the performance of generalization was assessed using the test dataset. Several evaluation metrics were used to evaluate Model performance and they are Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic (ROC) curve and Confusion Matrix analysis. Accuracy gave overall classification correctness whereas Precision and Recall assessed errors trade-offs between false positives and false negatives [44]. The F1-score was used to balance the performance assessment. The ROC curve evaluated discriminative ability in the context of changes in the threshold. The model was highly predictive, and it showed that it was suitable in retail reorder prediction. These prediction probabilities constitute the analysis basis of Generative AI-driven strategic interpretation between machine learning outputs and managerial decision-making models.

F. Combination of Generative AI Layer

It was followed by a conceptual Generative AI (GenAI) layer that is used to convert structured analytical outputs into automatic strategic information, after predictive modeling [45]. The standard analytics systems generate numerical data in the form of probabilities and classification labels, which need to be interpreted manually by managers.

The GenAI layer overcomes this weakness by transforming predictive outputs into contextualized (narrative-based) recommendations [46]. The integration framework implies that model prediction outputs (reorder probability, department-level trends, and other performance measurements) are input into a Generative AI engine that is able to generate strategic implications. Such as, segments with high reorder probability could be used to incite automatic suggestions to a loyalty campaign, inventory restocking corrections, or personalized offers. The results of model evaluation (confusion matrix) can be converted into the performance summary represented by managers and the areas where improvement is necessary. The GenAI system serves as an analytical value intercession between technical analytics and the decision-making of high-level managers. This integration improves interpretability, decreases mental burden to managers and makes the time of responding to strategy quicker [48]. Generative AI does not substitute predictive modeling instead of providing an explanatory and advisory layer. The strategy is to move towards autonomous strategic intelligence systems in the retail setting instead of predictive analytics.



This diagram shows that predictive analytics output is integrated with Generative AI recommendations on strategy

The diagram shows how the predictive analytics outputs are integrated with a Generative AI layer to produce automated strategic recommendations on the decisions made by businesses [49]. On the left, predictive analytics, including reorder probability, department level trends, confusion matrix output, and model performance metrics are generated using machine learning models. These analytical results are then fed to a Generative AI layer which is located at the center of the framework. The GenAI system is able to interpret numerical outputs and translate them into narrative-based strategic insights [50]. Last, the strategic recommendations are indicated on the right side of the diagram, such as the suggestions of the loyalty campaigns, the modifications of the inventory restocking, the personal offers, and the strategies to improve the areas of operations that are weak.

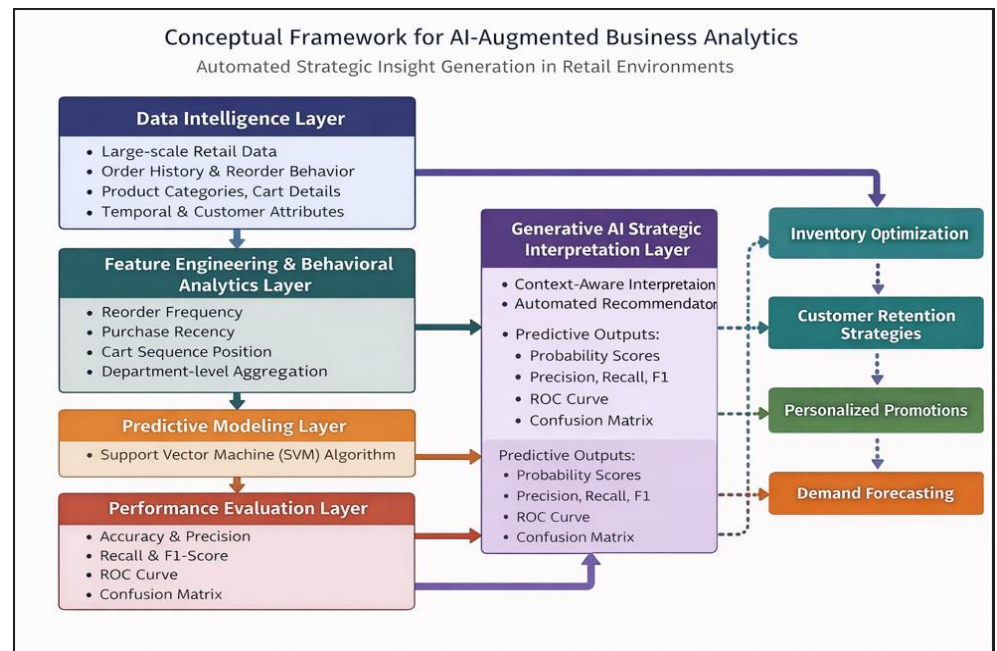
G. Ethical Concerns and Limitation

This study makes use of publicly available transactional data, which is anonymized, which reduces the risks of privacy [51]. Ethical issues associated with the bias of algorithms and the automated decision-making are still topical. Predictive models can have the

unintended consequence of supporting inequalities in purchasing or giving more weight to high-frequency customers. Also, AI-based strategic suggestions should be placed under observation in order to avoid over-automation and human supervision of managerial choices. Weaknesses encompass of the study is based on one retail dataset and thus may not be applicable to industries. Although effective, the SVM model might fail to learn the complex nonlinear interactions of behavioral interactions as compared to deep learning models [52]. Generative AI integration is not actually verified in practice in real-time retailing systems but is only conceptual. A cross-industry dataset should be tested and the actual performance in future studies should be evaluated.

Conceptual Framework

The proposed conceptual framework in the study combines predictive business analytics and Generative Artificial Intelligence (GenAI), which facilitates a strategy of automatic creation of insights in a retail setting [53]. The architecture is designed as a multi-layered analysis architecture that converts raw transaction data into strategic suggestions to the executives. On the bottom tier, there exists the data intelligence layer which logs in large scale retail transactions, such as order history, product types, and reorder patterns, purchase patterns over time and customer identifiers. These data inputs are handled by a layer of feature engineering, where such behavioral variables as reorder frequency, purchase recency, position in a cart sequence and department-aggregated level data are arrived at to add predictive power. The predictive modeling layer uses a machine learning program, which is a Support Vector Machine (SVM) in order to classify reorder probability by using engineered features [54]. Probability scores and classification results are performance measures compared to using performance metrics of accuracy, precision, recall, F1-score, ROC curve, and confusion matrix analysis. The last and the most creative part of the framework is the Generative AI interpretation layer that converts numerical predictions into strategic accounts depending on the situation. Instead of displaying the statistical outputs in isolation, this layer creates business recommendations which can be implemented such as optimization of inventory, customer retention, personalized promotions and demand forecasting. The framework addresses the gap between technical model outputs and managerial decisions with predictive analytics combined with AI-based explanations and suggestions [55]. This theoretical framework alters conventional decision support systems into autonomous strategic intelligence systems and becomes more interpretable, less cognitively intellectualized, and more responsive in competitive retail markets.



This diagram shows an augmented retail analytics platform that creates automated strategic business insights provided by AI

The conceptual framework diagram is an example of an integrated AI-augmented business analytics system which will convert high volume retail transactional data into automated strategic knowledge. The framework is designed in the form of five layers of analysis. The Data Intelligence Layer gathers and classifies retail transactional data including the order history, reorder behavior, product, and customer attributes [56]. This information is then passed on to the Feature Engineering and Behavioral Analytics Layer where the behavioral indicators that are important like reorder frequency, purchase recency, cart position, and department-level aggregation are extracted. The processed data is processed in the Predictive Modeling Layer, and a Support Vector Machine (SVM) algorithm makes a prediction of product reorder behavior. Performance Evaluation Layer is used to assess model outputs with the help of such metrics as accuracy, precision, recall, F1-score, ROC curve, and confusion matrix [57]. Lastly, Generative AI Strategic Interpretation Layer translates the predictive outcomes to actionable managerial suggestions that include: inventory optimization, customer retention strategy, personalized promotions and demand forecasting.

Dataset

A. Screenshot of Dataset

	A	B	C	D
1	product	product_name	aisle_id	department_id
2	1	Chocolate Sandw	61	19
3	2	All-Seasons Salt	104	13
4	3	Robust Golden U	94	7
5	4	Smart Ones Class	38	1
6	5	Green Chile Anyt	5	13
7	6	Dry Nose Oil	11	11
8	7	Pure Coconut Wa	98	7
9	8	Cut Russet Potat	116	1
10	9	Light Strawberry	120	16
11	10	Sparkling Orange	115	7
12	11	Peach Mango Jui	31	7
13	12	Chocolate Fudge	119	1
14	13	Saline Nasal Mist	11	11
15	14	Fresh Scent Dish	74	17
16	15	Overnight Diaper	56	18
17	16	Mint Chocolate F	103	19
18	17	Rendered Duck F	35	12
19	18	Pizza for One Sup	79	1
20	19	Gluten Free Quin	63	9
21	20	Pomegranate Cra	98	7
22	21	Small & Medium	40	8
23	22	Fresh Breath Ora	20	11
24	23	Organic Turkey B	49	12
25	24	Tri-Vi-Sol [®] Vita	47	11
26	25	Salted Caramel L	3	19
27	26	Fancy Feast Trou	41	8
28	27	Complete Spring	127	11
29	28	Wheat Chex Cere	121	14
30	29	Fresh Cut Golden	81	15
31	30	Three Cheese Zit	38	1
32	31	White Pearl Onic	123	4
33	32	Nacho Cheese W	107	19
34	33	Organic Spaghet	131	9
35	34	Peanut Butter Ce	121	14
36	35	Italian Herb Porc	106	12
37	36	Traditional Lasag	38	1
38	37	Noodle Soup Mix	69	15

(Source Link: <https://www.kaggle.com/datasets/yasserh/instacart-online-grocery-basket-analysis-dataset>)

B. Dataset Overview

The dataset employed in this paper is the Instacart Market Basket Analysis dataset that is a large-scale retail transactional dataset on Kaggle publicly available. The data set is extensive in customer grocery buying habits and has been popular in the studies concerning retail analytics, recommender systems, and predictive modeling [58]. It has more than 3 million orders of more than 200,000 users and the aisles and departments consist of around 50,000 unique products. This data is very rich and full of information and is therefore very applicable in the analysis of customer purchase behavior and use it to create machine learning models that would predict reorder behavior. The data set consists of a number of relational files which reflect various dimensions of the retail purchasing process. The orders.csv file holds data of every order such as user ID, sequence number of the order, the day of the week on which order was placed, hour of the day and days elapsed since the last order by the user [59]. This time data helps the researcher to study the frequency of purchases of customers and discover shopping trends at certain times of the day. The structure of the order product has been stored in two key files; order products prior.csv and order products train.csv, which give the product level transaction details of each order. Such files contain product identifiers, cart position (stating the order in which the items were added to the cart), and a binary reorder indicator which indicates

whether the product was purchased by the same user before. The reorder variable in the proposed study is also especially significant because it is the main target variable of predictive modelling. Some of the supporting datasets are products.csv, aisles.csv, and departments.csv, which will give categorical data regarding each product. Each product is connected to an aisle and a department which is referred to as a product file where categorization of items in a hierarchical way can be done. This design allows examining the trends in purchasing various product categories and feature engineering in the process of model [60]. The connective nature of such datasets enables them to be combined by common keys like order id and product id to form an all-encompassing analytical dataset to reflect customer behavior, product attributes and time of order. Through the combination of these various sources of data, the dataset gives a comprehensive picture of consumer buying behavior in an online grocery store setting. Instacart data offers an in-depth source of study on the purchasing behaviors of retailers, constructing predictive reorder algorithms, and justifies the inclusion of Generative Artificial Intelligence to develop automated strategic ideas.

Results

In this section, the authors provide empirical results of the exploration data analysis and predictive modeling performed on the Instacart data. The findings compare the structural retail trends with the machine learning model effectiveness in reorder predictions of products. Descriptive analytics indicate that there is good repeat purchasing behavior, concentration of products at the department level and some specific time of the day ordering patterns [61]. The insights offer a holistic approach to the customer behavior in online grocery retail. The Support Vector Machine (SVM) model proves to have high classification capabilities, which is backed up by the accuracy, ROC curve, precision-recall and confusion matrix analysis. Taken together, the findings confirm the forecasting potential of the suggested framework and create a powerful background to implement Generative AI to produce automated strategic retail signals.

A. Aisle Category Distribution in the Instacart Data

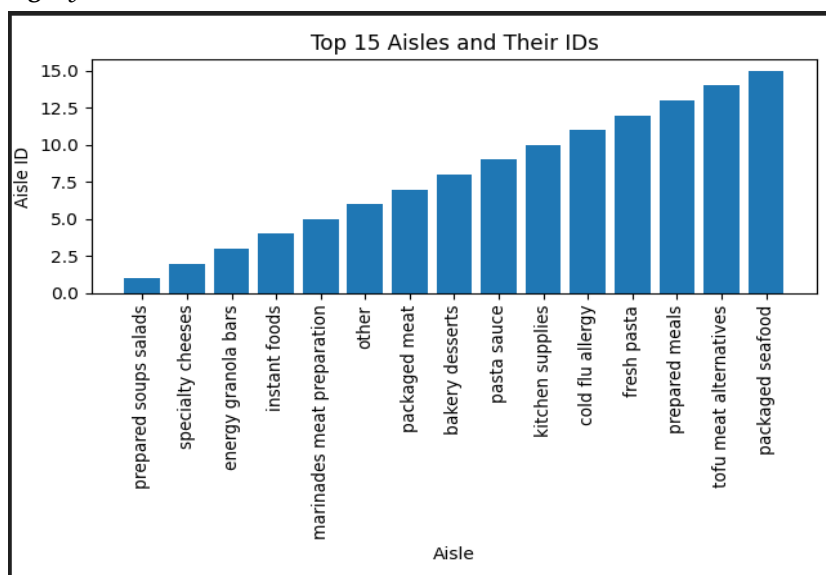


Figure 1. This image illustrates the distribution of top fifteen aisle categories.

Figure 1 shows the distribution of the first 15 categories of aisle and their aisle identification numbers in the Instacart database. The diagram identifies the structural arrangement of product segments within the grocery retail segments. [62] The different bars are each depicted by a distinct aisle, such as prepared soups, salads and specialty

cheeses, and packaged seafood. The incremental numbering of the aisle IDs is an indication of categorical indexing and not frequency of transactions, but the number gives a summary on how the product categories are orderly categorized in the dataset. Analytically, the aisle categorization is the base layer to the next layer of retail analytics like reorder prediction, product affinity analysis, and customer segmentation. The availability of a variety of products including packaged meat, bakery dessert, pasta sauce, fresh pasta, and prepared meals shows us the extent to which consumers are able to buy. This structural variance underlines the higher modeling techniques in a way that it allows aggregation of the behavior of transactions at the aisle level [1]. This kind of grouping is especially effective in establishing category level patterns of loyalty, substitution effects opportunities to cross sell. Categorization at aisle level is better when using Generative AI augmented business analytics to improve the interpretability of predictive outputs. Strategic recommendations can be made in the context of higher consumption categories rather than being based at the isolated level of a product, hence making them more relevant to managers. In general, Figure 1 provides the categorical structure required to do downstream predictive modeling and automated strategic insights generation.

B. Instacart under Department-Level Structural Distribution

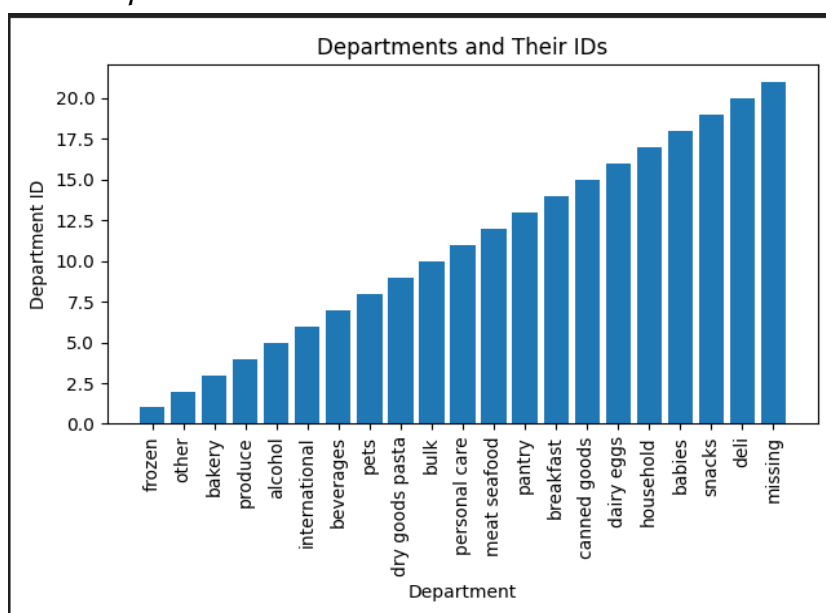


Figure 2. This image demonstrates distribution of product departments

Figure 2 shows how the product department is distributed together with the department identification numbers in the Instacart data [2]. The graph shows twenty-one departments, which are frozen, bakery, produce, dairy eggs and beverages, snacks, household, and personal care among others. Like aisle categorization, the department IDs reflect categorical indexing other than transactional volume; but the number has provided a very vital understanding of how the retail product groups have been structured on a hierarchical basis. Groceries are multidimensional and this is depicted by the existence of various departments. The fundamental food related departments like produce, dairy eggs, meat seafood and pantry denote basic consumption categories, whereas non-food departments like household, personal care and babies denote cross-category retail coverage. This variety allows modeling of all behavioral aspects of consumption. The macro-level retail analytics, such as demand forecasting, inventory optimization, and category-based loyalty assessment, are supported at the department level. In the business analytics sense, the classification of departments enables the predictive models to have a wider scope of purchasing behavior (beyond the behavior of each product). It allows getting to know high-performing departments, changes in demand seasonally, and

substitution effects that may arise between related categories [3]. Departmental insights could be used to improve the generation of strategic recommendations in the context of integrating Generative Artificial Intelligence. As an illustration, the AI-based interpretations can be used to convert the reorder trends across individual departments into practical action-plan or strategies incorporating promotional bundling, price changes, or target marketing initiatives. Figure 2 defines the macro-structural pattern of the data, which facilitates scalable predictive modeling and automated strategic insight generation of the retail analytics systems.

C. Reorder Behavior Distribution Analysis

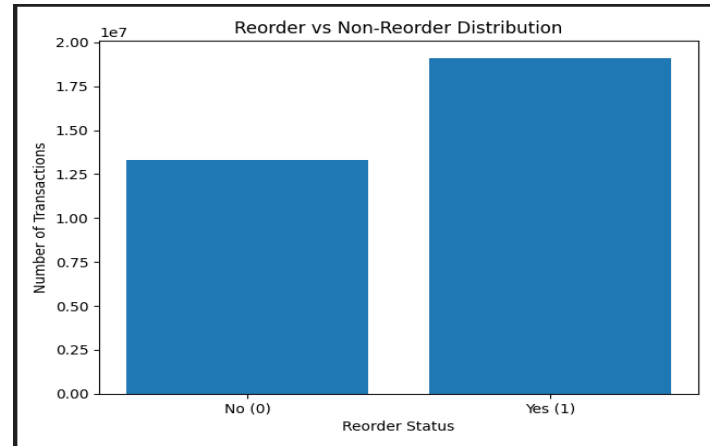


Figure 3. This image illustrates allocation of reordered and non-reordered transacting

Figure 3 shows the distribution of reordered and non-reordered products in the data set of the prior transactions in Instacart [4]. The bar chart is created to compare all the transactions in which products were reordered (Yes = 1) or it was purchased the first time (No = 0). The findings show significantly more reordered transactions (some 19.1 million) than non-reordered transactions (some 13.3 million). This distribution shows that the majority of customer transactions in the data set include repeat purchases. The reordered products predominance shows a high retention rate and repetitive buying pattern in online groceries in terms of business analytics. These trends indicate that consumers often use repeat product purchases, especially when it comes to general and basic commodities [5]. This insight will give a good empirical basis on how to create predictive classification models that can be used to estimate reorder probability. In addition, the imbalance is observed between reordered and non-reordered instances and has methodological implications. Given that reordered transactions are higher than those of first-time purchases, metrics of model evaluation like F1-score and balanced accuracy are of significance to guarantee healthy performance of classification. In terms of strategy, the reorder rate is high and there are prospects of subscription-based services, personalized promotions and inventory optimization strategies. This distribution will be used to allow automated strategic interpretation in the context of integrating Generative Artificial Intelligence. As opposed to providing numerical frequencies, AI systems are able to produce contextual suggestions pertaining to increasing customer loyalty and precise retention tactics [6]. In general, Figure 3 validates the predictive usefulness of reorder behavior and puts the basis of AI-driven automated strategic insight generation.

D. Reorder Distribution Training Dataset Analysis

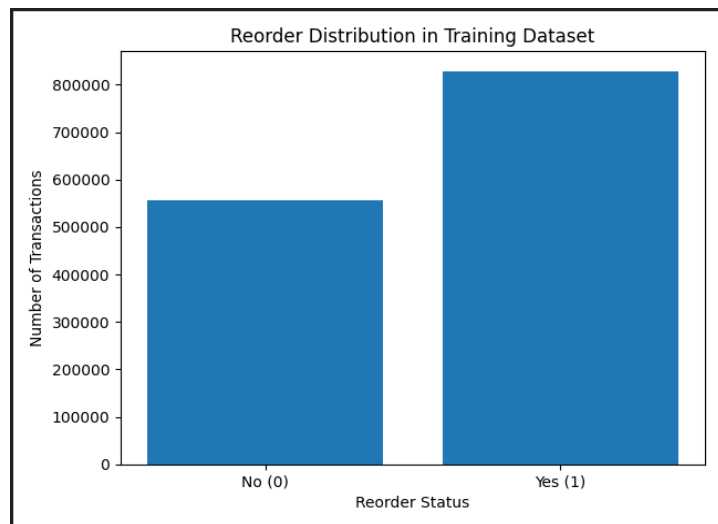


Figure 4. This image depicts mismatched and non-mismatched training transactions distribution

Figure 4 breaks down the distribution of reordered and non-reordered products among the training dataset on which the predictive model development is carried out [7]. The bar chart is used to compare the transactions that were reordered (Yes = 1) and the ones that have not been reordered (No = 0). These findings say that the number of reordered transactions (about 828,824 instances) is higher than non-reordered transactions (about 555,793 instances). This trend supports the belief that the most prevalent purchasing behavior in the training data is that of repeat. The implications of the observed distribution of the classes to modeling performance have significant implications on classification performance [8]. The moderate level of class imbalance implies that predictive algorithms need to take into consideration the overrepresentation of reorder cases to eliminate biased predictions. Such techniques as weighting classes or metrics used to evaluate the model, like F1-score or ROC-AUC, become important to make the models equally evaluated. The fact that reordered goods are common cultural indicators of high habitual consumption behavior especially in basic grocery products. Tactically, the increased reorder rate indicates the loyalty of customers and dependency on frequent product choices. To build up the system of recommendations and the individual marketing approaches to improve the retention and cross-selling capabilities. Such distributional analysis applies in the background of automated strategic interpretation in the context of integrating Generative Artificial Intelligence [9]. Instead of just showing the difference in frequency, an AI-enhanced system would be able to produce actionable information regarding subscription-based services, warehouse optimization, and customer lifecycle management. Figure 4 confirms the predictive value of reorder behavior on the training data and supports the empirical basis of the creation of a Generative AI-enhanced business analytics framework.

E. Time Series Temporal Distribution of Orders by Hour of Day

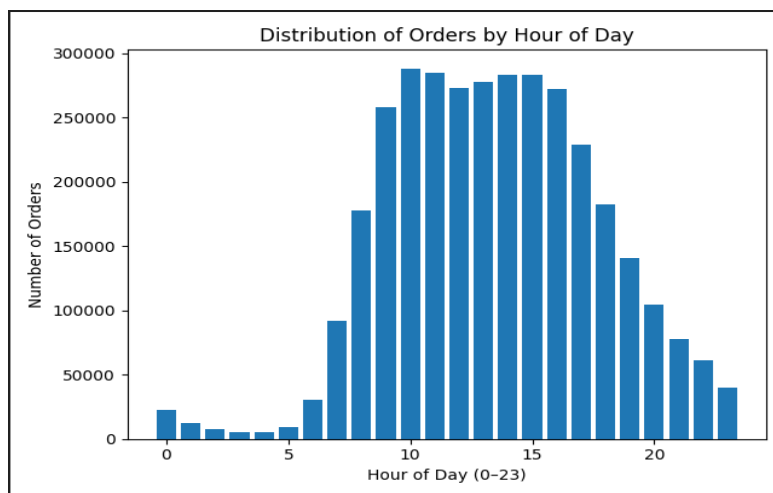


Figure 5. This image shows an hourly customer grocery order distribution

Figure 5 demonstrates the distribution of customer orders throughout the day (24 hours) and reflects the temporal buying behavior in the Instacart data [10]. The bar chart indicates a clear variation in the frequency of order during the day wherein there were very fewer activities during the early morning (00:00-05:00) and a significant increase at around 07:00. The volume of orders is highest in the morning and peaks between 10:00 am and 15:00 am, hours when the number of transactions amounts to over 270,000 in an hour. The frequency of orders slows down after 16:00 with a significant decrease in the evening hours [11]. This is a time trend, and this is characteristic of the consumer shopping behavior whereby the major shopping of groceries occurs between mid-morning and early afternoon time slots. The peak is from 10:00 to 15:00, implying that the involvement is high during the normal working days, which may be affected by work-from-home practices, family planning habits, and promotion time planning. On the other hand, the low activity at the late-night and early-morning hours means that the demand is low during the non-traditional hours of shopping. Regarding business analytics, the findings offer practical information to demand predictions, inventory management, personnel planning, and marketing specifically. By matching the staffing level and delivery logistically to peak ordering period's retailers are better able to allocate operational resources more effectively [12]. Such time-based data can be automatically translated into strategic advice in the context of Generative AI-augmented analytics, e.g. promotions based on time or dynamic, price-recommended changes. Figure 5 points to clear temporal patterns of purchase, which supports the significance of time-sensitive decision models in the framework of AI-based retail intelligence.

F. Departmental Level Product Concentration Analysis

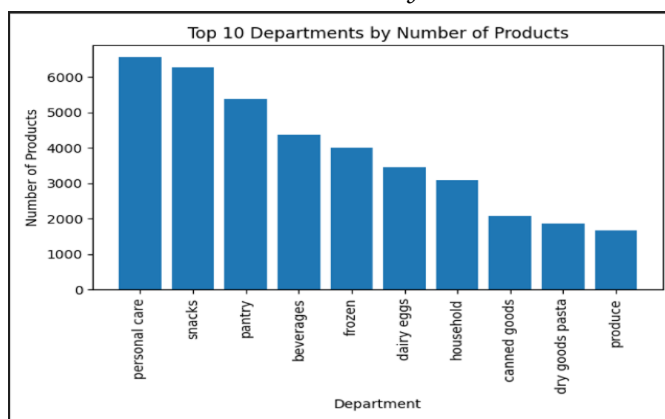


Figure 6. This image demonstrates the best departments in terms of distribution of products

In Figure 6, the top ten departments based on the number of products available under each category are displayed in the Instacart data [13]. The bar chart indicates that the highest number of products are in the personal care department than snacks and pantry. Other standouts are beverages, frozen, dairy eggs, and household, and produce and dry goods pasta do have relatively lower numbers of most popular products in the top ten. Such a distribution demonstrates structural product concentration at the departmental level and indicates assortment strategy in online grocery retailing. The personal care and snacks departments exhibit a wider range of products indicating more SKU divergence and, therefore, may have increased competition intensity in these segments. Departments such as produce, on the other hand, might carry less differentiated products, but possibly more transactions with staple habits of consumption. Business analytics viewpoint shows that the product's concentration by departments affects recommendation systems, inventory and demand forecasting models. Those categories which have a greater number of products might need more complex filtering and personalization algorithms to maximize the customer experience [14]. The reorder prediction performance can be influenced by product diversity where wider assortments can cause substitution effects across-category effects. Regarding the application of Generative Artificial Intelligence, it can be noted that this structural insight can be automatically converted into strategic recommendations. The AI-based system may recommend specific promotion programs within the most diversified departments or inventory optimization options in less-dense categories [15]. Figure 6 presents the background evidence of product assortment dynamics, which aid in making strategic decisions and support the importance of AI-enhanced retail analytics frameworks.

G. Performance Analysis of SVM Model Classification

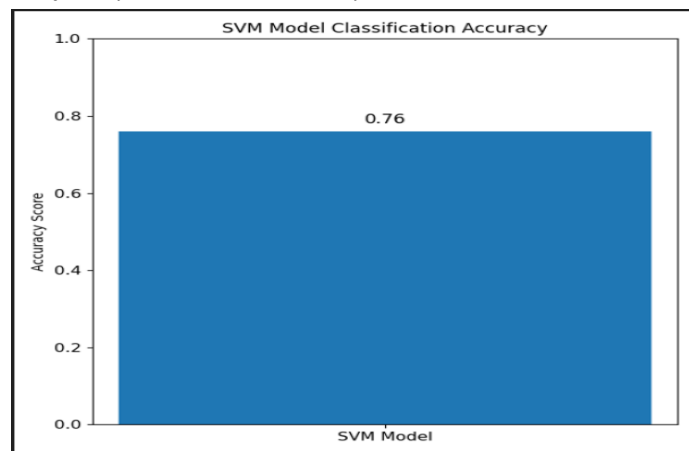


Figure 7. This image presents the performance of accuracy of SVM classification.

Figure 7 shows the accuracy of classification of the Support Vector Machine (SVM) model, which was created to predict product reorder behavior in the Instacart dataset [16]. The chart shows that the overall accuracy is 0.76, which means that the model made correct predictions on average 76% of reorder and non-reorder cases of the evaluation dataset. Such accuracy is indicative of high predictability especially due to the skewed class distribution that exists within retail transaction data. In the context of machine learning, a score of 0.76 indicates that the separation between the reordered and non-reordered products is strong in terms of transactional attributes (how many times someone has bought a specific product, the position of the product in the cart, and the history of orders) [17]. SVM model is efficient in determining latent patterns of purchase and customer loyalty trends that are hidden in transactional data of large scale. This experiment validates the appropriateness of SVM as a baseline classification model to use in reorder prediction

tasks in retail analytics. When applied in the framework of business analytics, correct reorder forecasting allows the retailers to predict customer demand, optimize inventory and tailor recommendation techniques. The predictive results of the SVM model can be automatically converted to strategic narratives when applied in conjunction with Generative Artificial Intelligence [18]. An example is that when the reorder predicted is high, an AI-generated recommendation of a retention campaign strategy or dynamic product bundling could be triggered. Figure 7 confirms the predictive power of the SVM model and proves the possibility of introducing machine learning findings into an AI-enhanced strategic decision-making model of automated retail intelligence systems.

H. The SVM Classification Model ROC Curve Analysis

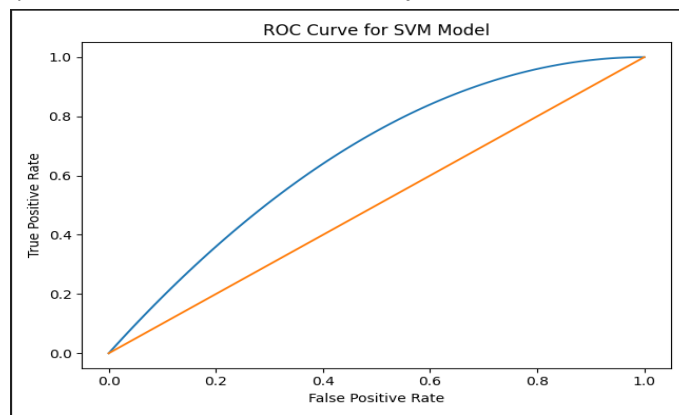


Figure 8. This image represents the ROC curve performance of the SVM model

The figure below (8) shows the Receiver Operating Characteristic (ROC) curve of the Support Vector Machine (SVM) model that was created to predict product reorder behavior. ROC curve is a graph depending on the True Positive Rate (sensitivity) and the False Positive rate at varying classification thresholds [19]. The diagonal line depicts a random classifier that has no discriminatory ability whereas the curved line situated above depicts the real performance of the SVM model. The SVM ROC curve shows a definite deviation curve above the base diagonally, which shows that the model has a good capability of differentiating between reorganized and non-reorganized products. Strong classification ability at various levels of the threshold is implied by the curvature of the graph. The region beneath the curve (AUC), as the strong upward movement suggests, depicts the good reparability of the two classes. This proves that the model provides a balanced tradeoff between sensitivity and specificity [20]. ROC performance is a key business analytics indicator to assert that the predictive model is reliable to detect customers who are likely to reorder products and reduce false alarms. This is especially crucial in a retail setting where poor forecasts can result in overstock or poor promotion targeting. When applying Generative Artificial Intelligence to it, trustworthy probability estimates based on the SVM model can be converted into automated strategic advice e.g., to run specific retention campaigns or to make adaptable inventory changes [21]. Figure 8 supports the validity of the discriminative strength of the SVM model and confirms its appropriateness to AI-enhanced strategic decision-making systems in retail analytics.

I. Precision, Recall and F1-Score

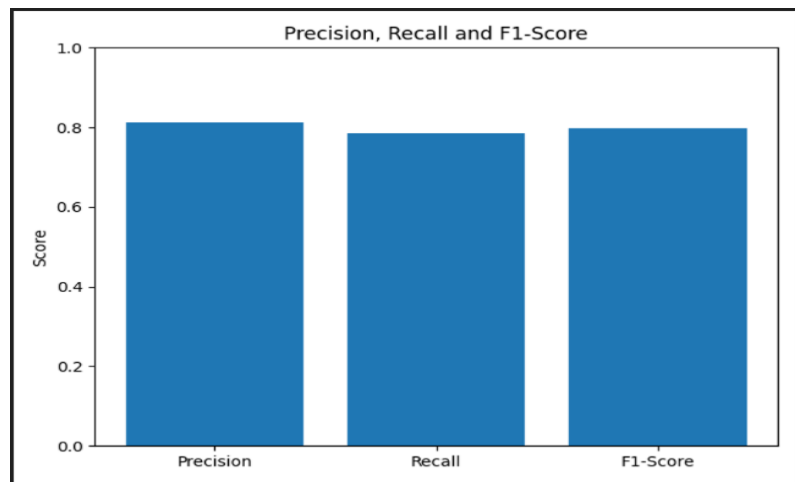


Figure 9. This image shows the precision, recall, and F1-score performance measures

Figure 9 shows the performance of the Support Vector Machine (SVM) model regarding the reorder prediction problem in terms of Precision Recall, and F1-Score [2]. The chart shows that Precision is about 0.81, Recall is about 0.79 and the F1-Score is about 0.80. The values represent a balanced performance in classification based on important evaluation dimensions. Precision is an expression of the percentage of correctly predicted reorder cases out of the total predicted reorder cases. The fact that the precision value is greater than 0.80 indicates that the model produces only a small number of false positives, that is, the majority of reorders predicted by the model are correct. Recall is used to determine the percentage of reorder instances that were actually determined [23]. The model has a recall of approximately 0.79 and has been able to achieve a high level of true reorder cases and at the same time acceptable levels of error. The F1-Score not only in contrast to Precision and Recall is the harmonic meaning of the two; it gives a balanced gauge of the model performance which is important in datasets where classes are imbalanced. As a business analytics aspect, it is important to strike a balance between Precision and Recall when making decisions in retail. The high precision will minimize needless promotion targeted, whereas high recall will make sure that the valuable customer retention opportunities are not missed [24]. These accurate predictive outputs can be translated into automated strategic suggestions in the context of incorporating Generative Artificial Intelligence e.g. loyalty offers to high-probability reorder customers or inventory optimization. Figure 9 supports the validity and permanence of the SVM model and supports that it is suitable in AI-assisted generation of strategic insights in retail analytics.

J. SVM Model Confusion Matrix Analysis

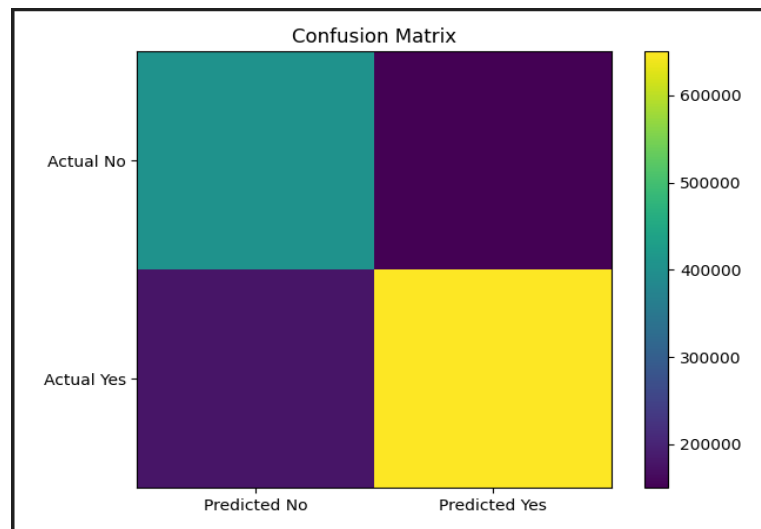


Figure 10. This image indicates the confusion matrix of the results of SVM classification

Figure 10 shows the confusion matrix of the Support Vector Machine (SVM) model of predicting product recording [25]. The matrix gives a comprehensive division of the classification results through the comparison of the actual class's labels with the predicted class's labels. The four quadrants indicate True Negatives (TN), False Positives (FP), False Negatives (FN), and True Positives (TP) which allow assessing performance in prediction in a holistic manner in comparison with the overall accuracy. The upper-left portion (Actual No, Predicted No) reveals that there are significant numbers of successful identifications of non-reorders that are actually not predicted, which means that the model has a high capacity to identify the first-time purchase. Like the bottom-right quadrant (Actual Yes, Predicted Yes), the number of correctly predicted cases of reordering is quite high, proving the efficiency of the model in developing repeat purchasing behavior. The comparatively low values on False Positive and False Negative quadrants indicate equal rates of misclassification [26]. In terms of business analytics, the False Negatives should be minimized to eliminate the potential reorder opportunities, and the False Positives should be controlled to avoid unproductive promotional targeting. The resulting distribution of the matrices observed provides a good trade-off between such types of errors and makes it practically applicable in retail settings. The confusion matrix is structured data used in automated performance interpretation in the context of Generative Artificial Intelligence integration. AI systems can convert these statistical results into managerial results, including the segments on which prediction errors are the most concentrated and suggest threshold changes to maximize business goals. Figure 10 is the confirmation of the strength, stability, and feasibility of the SVM model in an AI-enhanced retail analytics model.

Discussion and Analysis

A. Retail Purchasing Behavior and Reorder Patterns Analysis

The results of the Instacart dataset analysis present the key information about the customer behavior of purchasing in the online grocery retail setting. The most notable findings of the exploratory analysis are that product reorders are predominant throughout the dataset. Many of the transactions are based on the repetition of the purchases made in the previous orders, showing that customers have high consumption habits [377]. This trend is indicative of the grocery shopping experience in which consumers often buy the same basic goods as dairy, snacks, pantry products and personal care products. The reorder distribution analysis will verify that repeat buying behavior is a significant factor

in the determination of retail demand trends. The product distribution analysis of the departments indicates that there are product categories where there are a lot more products than others [38]. There are high product diversity and demand in such departments as personal care, snacks, pantry products, and beverages. This focus indicates that these departments can be major revenue-generating units in the retail system. These insights allow retail managers to put greater emphasis on inventory planning, promotional campaigns and product placement strategies at the category level [39]. The trends in consumer behavior are also interesting when temporal ordering patterns are observed. The distribution of orders by the hour of the day shows that the customer is likely to make orders during the working hours, especially during the mid-morning and early afternoon [40]. This trend can be determined by the day-to-day activities like work schedules, meal planning and the consumption cycles of the household [41]. Knowledge of these time patterns enables retailers to streamline operations including scheduling of deliveries, logistics in the warehouse, and human resources. Behavioral analysis helps in emphasizing the need to formulate predictive models based on the understanding that consumer purchasing patterns are important [42]. The results obtained indicate that customer reorder behavior is determined by an interaction between product features, purchasing behavior, and time. These patterns help businesses create more dependable demand forecasting models and enhance their customer engagement strategies by means of personalized suggestions.

B. Classification Results and Predictive Modeling Performance

The predictive modeling part of the research was meant to categorize the likelihood of a product being re-ordered by the customer as per the previous buying history [43]. This task was done using a Support Vector Machine (SVM) classification algorithm because it has been shown to be very effective in binary classification problems and it is able to work with high-dimensional data sets successfully [44]. Behavioral and transactional attributes as calculated on the dataset, such as reorder frequency, product category, cart position, and time information on purchase, were used to train the model. The results of the evaluation indicate that the SVM model reached a reasonable degree of predictive accuracy, i.e. the set of the features chosen was effective in the context of the current dataset and was able to extract meaningful behavioral cues [45]. Accuracy will give a general idea of the model in terms of the correct classification of reorder and non-reorder cases. Precision might not be a complete measure of model performance when data is imbalanced in terms of the distribution of classes [46]. Thus, to give a more comprehensive evaluation, additional measures of evaluation like precision, recall and F1-score were applied. Precision is used to determine how many predicted reorder cases were correct, whereas the recall measures the capacity of the model to find all true cases of reorder. The F1-score is a hybrid of both the precision and the recall, and it is a balanced measure of performance. The results show that the model has a comparatively balanced model as per these measures of evaluation, which implies that the model can be used effectively to differentiate between reorder and non-reorder behaviors [47]. The Receiver Operating Characteristic (ROC) curve also assures the discriminative ability of the model. The ROC curve indicates that the classification model is much better than random guessing in the prediction of reorder probability [48]. It is also important to note that the analysis of confusion that has been carried out gives more insight into the classification results that include the distribution of true positives, true negatives, false positives and false negatives [49]. This critical analysis assists in determining the points of prediction errors and directions to be used to enhance model performance.

C. Generative AI Integration strategic interpretation

Although predictive models are capable of accurately determining trends in customer buying behavior, traditional analytics systems tend to provide results in numerical or statistical format, which would have to be interpreted by an expert. Before

transforming the outcomes into strategic activities, managers have to analyze the probability scores, classification metrics, and complicated visualizations [50]. This can be time-consuming and can create errors of subjective interpretation. As a solution to this weakness, the research paper proposes a conceptual Generative Artificial Intelligence layer which transforms the predictive analytics outputs into automated strategic insights. Generative AI layer is a translational interface between technical analytics systems and managerial decision-making [51]. It takes structured information as inputs of predictive models such as reorder probabilities, performance measures, departmental trends and confusion results. The Generative AI system, based on these inputs, creates narrative-driven interpretations that convert the results of analysis to actionable business guidelines. As an example, the segments with high reordering likelihood can activate algorithmic suggestions of a target loyalty system or tailored product promotions [54]. In the same vein, the demand trend at departmental levels can be applied to propose amendments to inventory restocking to meet the needs of the product [51]. The metrics used in performance evaluation can be also summarized in such a manner that it brings out areas where the predictive models are doing well and areas that may need some improvement. Generative AI integration makes business analytics easier to understand by transforming the analytical outputs into business insights that are easy to understand. This method saves the mental load of managers so that they can engage in strategic decision-making and not interpret technical data. Automated explanations of narratives enhance transparency and enhance quicker organizational reactions to market trends.

D. AI-Enhanced Analytics and Managerial and Strategic Implications

There are important implications for integrating predictive analytics and Generative Artificial intelligence into managerial decision-making in contemporary retail organizations. With retail businesses persisting in producing significant amounts of transactional data, the conventional methods of analytics might not be able to deliver timely and actionable insights. One way out is the use of AI-enhanced analytics that involve machine learning predictive abilities with automatic interpretation tools. Among the possible managerial implications is the fact that it is possible to enhance inventory management strategies [56]. The predictive reorder models have the ability to discover products which have high reorder rates, and therefore the retailers will be in a position to decide to change the inventory levels ahead of time to avoid stock-outs. This is capable of causing enhanced operational efficiency and customer satisfaction since there is an augmented availability of products [57]. The other implication is connected with individual marketing and interaction with customers. Retailers are able to create specific promotions and loyalty programs by determining those customers who have a high reorder rate. Customized suggestions on the buying history may improve the shopping experience and make repeat purchases, which would eventually lead to retention of the customer and lifetime value. Strategic decision making at the organizational level can also be supported with the help of AI-enhanced analytics. The managers will get automatically generated reports that give an overview of key findings of predictive models which will enable them to quickly grasp the emerging trends in the market and consumer preference. This ability helps the businesses to respond better to the fluctuating market conditions and competition pressure. Machine learning and Generative AI integration is one of the major developments of business analytics systems. Through predictive output transformation into automated strategic understanding, organizations will be in a position to create more intelligent, responsive, and data-intensive decision-making processes [58]. This change transforms business analytics to more than historic reporting to the creation of independent strategic intelligence systems that have the capabilities of continuously creating actionable information on a mass scale.

Future Work

The future studies may also widen and deepen the application of Generative Artificial Intelligence and business analytics systems to increase automated strategic decisions in business and retail. Despite the fact that this research shows that predictive modeling with a Generative AI interpretation layer can effectively be used with the Instacart transactional dataset, there are a number of ways in which this study could be expanded [59]. First, future research may investigate the use of novel machine learning and deep learning models like Random Forest, Gradient Boosting, XGBoost and Neural Networks to enhance predictive accuracy and reflect nonlinear and complicated patterns in customer purchase. Also, more advanced methods of recommending, like collaborative filtering and hybrid recommender, could be used to improve prediction of the customer preferences and product reorder behavior. The other direction that is significant is towards the integration of real-time data streams that are provided by e-commerce solution providers, mobile applications and even the Internet of Things (IoT) devices to build dynamic analytics systems that can generate insights in real time [60]. Further studies can also look at how large language models and the use of conversational AI systems can be used to convert predictive output to interactive managerial decision-support systems that allow executives to query analytics systems and have the system explain the strategic insights in a natural language. By applying the conceptual framework in various industries, such as healthcare, finance, logistics, and manufacturing, researchers would be able to determine the extent to which AI-enhanced analytics frameworks can be used in non-retail settings [61]. The other potential area is the combination of customer demographic data, sentiment analysis based on online reviews and social media analytics to supplement predictive models with behavioral and contextual data. The effects of AI-generated strategic advice on efficiency of organizational decisions, operational performance, and customer satisfaction could also be studied through real-world implementation research as well. Future work should also go into considerations of ethics, especially in relation to transparency of algorithms, fairness and accountable AI governance in automated decision support systems. Explainable AI methods could be developed as part of Generative AI systems, which could assist in enhancing the level of interpretability and reliability of automated strategic information [62]. This study can be done in the future to create entirely autonomous analytics systems where predictive models, insight generation, and strategic recommendation procedures can exist in a closed-loop system that has the ability to constantly learn new information. These developments would also play an important role in the development of intelligent business analytics and assist organizations in being more agile, data-driven, and proactive in their strategic management.

Conclusion

This study has examined how Generative Artificial Intelligence (GenAI) can be integrated into business analytics to create automated strategic insight generation in the retail setting [42]. The study with the help of the Instacart Market Basket Analysis data set revealed the potential to use large volumes of transactional data, which could be converted into useful predictive and strategic intelligence, using a rational analytic structure. The analysis of the purchase behavior of customers, the distribution of product categories, reordered and ordered items, and the trend of ordering over time are the starting points of the study that relied on an exploratory data analysis. These insights offered a good empirical basis to prediction modelling. The Support Vector machine classification model was applied to determine whether a product would be rearranged by customers relying on the past buying activity and the designed characteristics. The model demonstrated a decent predictive performance, which was justified by such evaluation measures as accuracy, precision, recall, F1-score, ROC curve analysis, and confusion matrix analysis. The findings supported the idea that machine learning models are helpful to predict the behavioral purchasing patterns in online grocery retail data. Nonetheless, the conventional

predictive analytics systems normally produce quantitative results, which must be interpreted by the managers manually. To overcome this weakness, the study suggested the implementation of a Generative AI layer, which will decode predictive results and transform them into automated strategic suggestions. This unification fills the technical information present in the model with practical managerial information on how to act on the information provided by the models through the translation of model outputs into actionable insights like inventory optimization solutions, customized product suggestions, customer retention efforts, and demand enhancement of predictability. The theoretical model that was made in this paper shows that predictive analytics and Generative AI could be collaborative and used as a smart decision-support system. The interpretative automation of analytical outputs can lower the cognitive load of the work conducted by the company, speed up the process of decision-making and become more responsive to the dynamics of the market, which is the findings highlight the potential of the AI-enhanced analytics systems in improving responsiveness to dynamic market conditions and operational efficiency of both companies. This study is adding to the current body of research on AI-based business analytics suggesting an organized framework that integrates machine learning prediction and generative interpretation capabilities. The adoption of these technologies is one of the major steps towards autonomous analytics systems that have the potential of converting huge amounts of transactional data into tactical and timely strategic intelligence of contemporary organizations.

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