International Journal of Industrial Engineering
2026;10(1):11-19.
ISSN: 2456-8449

Business Intelligence-Driven Analysis of Airline Passenger Satisfaction Using SAS Enterprise Miner

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Abstract: Business intelligence is essential for converting corporate data into meaningful insights for strategic decision-making. This research presents an advanced data mining architecture using SAS Enterprise Miner to examine customer satisfaction trends for business intelligence purposes. The experimental assessment used a publicly accessible Kaggle dataset including airline passenger service and demographic data. The dataset comprises essential factors such as Age, Flight Distance, Departure Delay, Arrival Delay, Class, Type of Travel, and several service rating criteria such as Inflight Wi-Fi Service, Seat Comfort, Food and Drink, and On-board Service, assessed on a 1–5 scale. Data preprocessing methods, such as missing value imputation, categorical encoding, and normalization, were implemented before model construction. Classification algorithms were developed to forecast passenger satisfaction levels and identify significant business factors. The model's performance was assessed using accuracy, precision, recall, and AUC metrics. The findings indicate that sophisticated data mining methodologies in SAS Enterprise Miner effectively reveal essential service quality metrics, facilitating data-informed decision-making and improved business intelligence approaches.

Keywords: Data mining, Predictive analytics, Business intelligence, SAS enterprise miner, Big data

INTRODUCTION

In today's data-driven world, organisations must extract valuable insights from massive amounts of data. Effective complex dataset analysis is crucial for informed decision-making, competitive advantage, and operational efficiency. SAS Enterprise Miner, a premier data mining and business intelligence software package, provides a complete set of capabilities to help customers maximise their data. Using statistical analysis, machine learning, and data visualisation, SAS Enterprise Miner helps organisations understand data mining and get actionable insights. SAS Enterprise Miner's main purpose is to provide robust data mining procedures for varied business purposes. A user-friendly interface streamlines data mining, making predictive model building, validation, and deployment easy. SAS Enterprise Miner simplifies data analysis by combining data preparation, exploration, and modelling. This comprehensive environment enables data analysts and business professionals at all skill levels, promoting data-driven decision-making throughout the organisation. Implementing SAS Enterprise Miner improves corporate predictive analytics. Decision trees, neural networks, and clustering algorithms are included in the software to solve many commercial problems. This enables organisations to do complicated analytics like client segmentation, fraud detection, and risk assessment. SAS Enterprise Miner lets customers customise their analytical methods to business challenges, improving forecasts and strategic choices. These sophisticated analytical methods are seamlessly integrated, allowing organisations to anticipate market trends and client behaviour.

SAS Enterprise Miner is a data mining and business intelligence ecosystem, not just a tool. The program uses data analysis best practices to help users get insights. SAS Enterprise Miner emphasises data governance to preserve data quality and compliance during data mining. Users may improve their analysis' credibility by adding data management tools to guarantee correct and trustworthy data. The program supports project sharing and version control for user collaboration. Collaboration on data mining initiatives fosters knowledge exchange and cross-functional insights. SAS Enterprise Miner lets organisations leverage their teams' knowledge to create more creative ideas and better results by promoting cooperation. SAS Enterprise Miner's machine learning and AI enhance its superior data mining capabilities. These technologies allow users to create complex models that adapt

Received: 11.11.2025 Revised: 08.01.2026 Accepted: 17.01.2026

to shifting data patterns and improve predicted accuracy. These strategies evolve to keep organisations at the vanguard of data analytics, ready to confront new issues and seize new possibilities.

CMSR Data Miner, Knowledge STUDIO, and RapidMiner Tools for Data Mining [1]. A comparative study examined the performance of CMSR Data Miner, Knowledge STUDIO, and RapidMiner tools. These tools were evaluated for their ability to handle large datasets, accuracy in predictive modelling, and user efficiency. Machine Learning Techniques for Health Insurance Premium Pricing [2]. Machine learning methods have proven beneficial for pricing health insurance premiums. This research explored the effectiveness of several machine learning algorithms in predicting insurance premium rates based on customer profiles and historical data. Predicting Student Dropout Using Data Mining in Private Institutions [3]. A data mining approach was utilized to predict student dropouts in private higher education institutions in Malaysia. The study applied machine learning algorithms to analyse demographic and academic factors contributing to dropout rates. e-Commerce Product Recommendations Using Customer Behaviour Data Mining [4]. An investigation into customer purchasing behaviour was conducted to improve product recommendations for e-commerce platforms. The analysis applied data mining techniques to track and analyse customer interactions, preferences, and purchase history.

Data Mining Strategies to Improve Profitability in the Insurance Industry [5]. The insurance sector is increasingly turning to data mining strategies to improve profitability. Assessing Enterprise Mortality in Slovakia's Business Environment [6]. A study examined the factors contributing to the closure of businesses in Slovakia. Using statistical methods, the research analysed the economic, political, and social challenges faced by enterprises in the region. Recommendations for policy changes include reducing regulatory burdens and offering financial support. ChatGPT as a Tool for Teaching Statistics and Data Analytics [7]. The use of ChatGPT in teaching statistics and data analytics was explored as an innovative educational tool. The study evaluated how artificial intelligence (AI) models like The Role of Regression Algorithms in Data Mining Application [8]. The application of regression algorithms in data mining was examined in a business analytics context. Regression models, including linear, logistic, and polynomial regression, were used to uncover relationships between variables and make predictions in datasets.

Social Media's Influence on Green Consumption: A Text Mining Approach [9]. Text mining techniques were applied to investigate how social media impacts public attitudes toward green consumption. Risk Mitigation through Predictive Analytics Across Various Industries [10]. Predictive analytics was evaluated for its application in risk mitigation strategies across multiple industries. Artificial Neural Networks in Business Analytics Projects [11]. The role of artificial neural networks (ANNs) in business analytics projects was explored, focusing on their ability to handle complex data patterns and provide accurate predictive models. Predicting Outpatient Ultrasound Examination Time with Data-Driven Techniques [12]. Data-driven techniques were applied to optimize the scheduling of outpatient ultrasound examinations in a multi-clinic environment.

Advanced Analytics for Financial Fraud Detection [13]. The use of advanced analytics for detecting financial fraud was explored, focusing on leveraging machine learning techniques to identify suspicious activities. Early Detection of Cardiac Arrest with Data Mining Algorithms [14]. Data mining algorithms were used to predict cardiac arrest in patients by analysing medical data, including vital signs, medical history, and test results. Data Mining Applications in the Securities Market [15]. The application of data mining techniques in the securities market was examined, with a focus on identifying market trends, predicting stock prices, and analysing trading patterns. Data Mining Software Tools in Business Analytics [16]. Several data mining software tools were evaluated for their effectiveness in business analytics. Tools such as R and Python were assessed based on their ease of use, scalability, and ability to handle large datasets.

Foundation Model Projects and Their Emerging Characteristics [17]. Foundation model projects are gaining traction due to their ability to handle large-scale, complex data operations. Customer Purchasing Behaviour Data Mining for Product Recommendations in e-Commerce [18]. E-commerce platforms have increasingly turned to customer purchasing behaviour analysis to improve product recommendations. Eliciting Requirements Using Design-Thinking and Computational-Thinking Approaches [19]. The process of requirements elicitation was explored using both design-thinking and computational-thinking approaches. The study compared how each methodology contributes to gathering user needs during the initial stages of system development. Zero-Inflated Tweedie Models for Insurance Claim Data Analysis [20]. A statistical approach using zero-inflated Tweedie models was employed to analyse insurance claim data. The model was developed to handle datasets with excess zeros, typical in insurance claims where many policyholders do not file claims.

PROPOSED SYSTEM

SAS Enterprise Miner is famous for its data mining and business intelligence capabilities. The platform's easy interface and extensive variety of algorithms help extract meaningful insights from big datasets. Its reliable data cleaning, transformation, and normalization functions assure excellent mining data quality. From Figure 1, this block diagram shows SAS Enterprise Miner data ingestion and preparation. Data is imported from relational databases, flat files, and cloud storage systems in the architecture. Data purification, transformation, and feature selection follow in SAS Enterprise Miner. Early data preparation is essential for improved data mining.

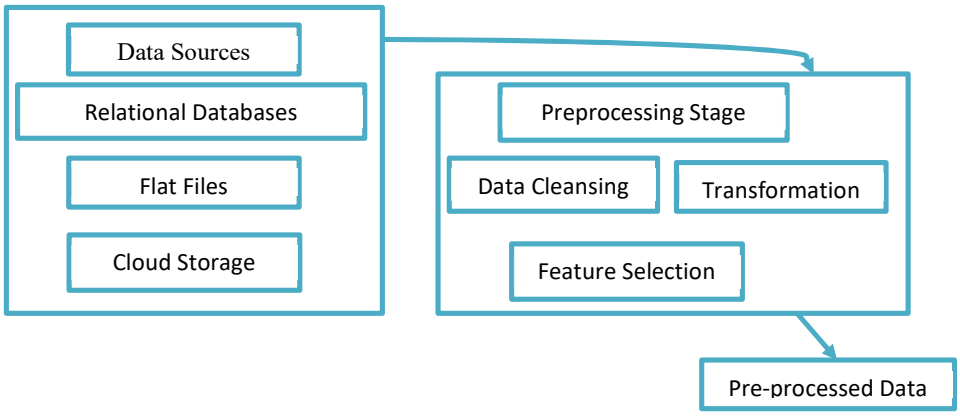

Figure 1. Data Import and Preprocessing with SAS Enterprise Miner

From risk management to consumer behaviour prediction, SAS Enterprise Miner excels in predictive modelling. Decision trees, neural networks, and support vector machines (SVMs) are supported, making the platform adaptable for predictive analytics workloads. Users may study historical data and predict future occurrences using its model-building skills. Figure 2 diagram shows SAS Enterprise Miner model construction and training.

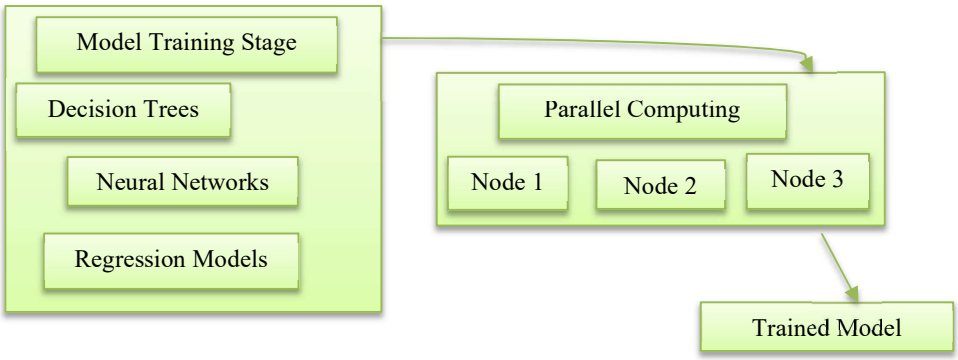

Figure 2. Model Building and Training in SAS Enterprise Miner

The architecture shows how decision trees, neural networks, and regression models are formed. For performance optimisation, these models are trained utilising pre-processed data and parallelised. SAS Enterprise Miner has several model selection tools and algorithms for designing strong predictive models for business intelligence applications. SAS Enterprise Miner turns raw data into actionable business intelligence (BI) insights. It integrates data mining with BI technologies so firms may optimize decision-making using sophisticated analytics. SAS Enterprise Miner gives firms a competitive advantage by providing clear insights into complicated datasets with built-in reporting and visualization. Figure 3 shows SAS Enterprise Miner's final assessment and deployment block diagram. After training, cross-validation and performance measures like accuracy, recall, and ROC curves evaluate the models. The top models are used for real-time business intelligence. SAS Enterprise

Miner interfaces with business intelligence systems for real-time prediction-based data-driven choices. This design shows how SAS Enterprise Miner helps businesses deploy accurate and efficient models. Figure 4 shows how SAS Enterprise Miner is used for sophisticated data mining and business intelligence.

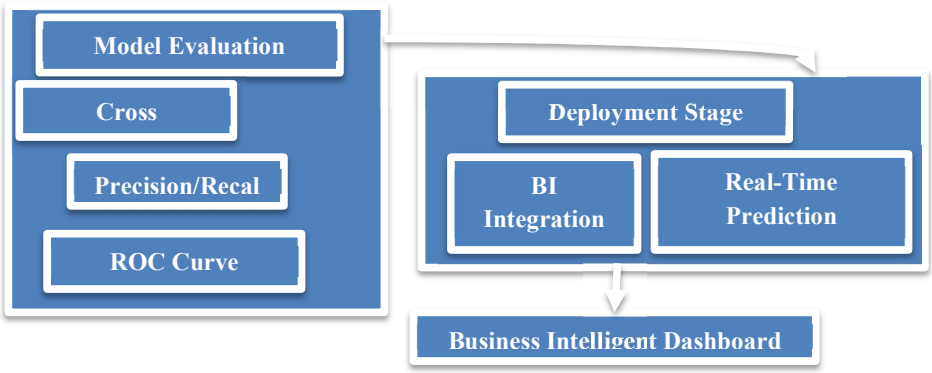

Figure 3. Evaluation and Deployment of Predictive Models using SAS Enterprise Miner

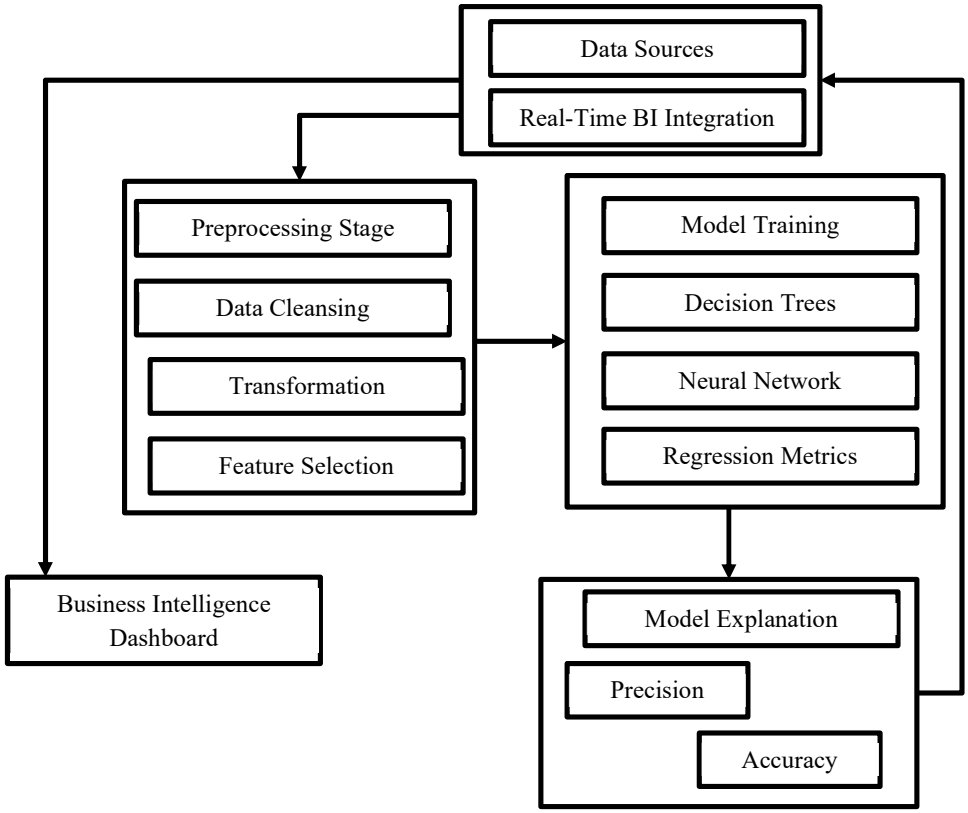

Figure 4. Data Flow Diagram for Utilizing SAS Enterprise Miner in Business Intelligence

With its extensive text mining capabilities, SAS Enterprise Miner excels at handling unstructured data. Unstructured data like social network postings, emails, and customer feedback may provide firms important insights into consumer mood and preferences. SAS Enterprise Miner rapidly processes vast amounts of text data into structured representations for analysis. Customer segmentation is essential for focused marketing and customized service. SAS Enterprise Miner's clustering algorithms may divide vast consumer bases by behaviour, preferences, and demographics. By recognizing these categories, organizations may adjust marketing, product,

and customer service to distinct client groups. SAS Enterprise Miner uses K-Means to cluster customers by attribute similarity. Retailers may segment customers by purchasing history, age, and region. Analysing these divisions may help create targeted advertising, product positioning, and consumer loyalty programs. SAS Enterprise Miner's clustering functionality goes beyond demographic segmentation to reveal more complex consumer behaviour patterns. This improves marketing efforts and budget allocation. The platform's scalability lets these models be applied to big datasets, keeping segmentation effective as client bases increase.

Data is collected from relational databases, flat files, and cloud storage to start the process. Preprocessing comprises data purification, transformation, and feature selection. Data is pre-processed and utilised to train decision trees, neural networks, and regression models. These models are assessed on accuracy and precision. The top models are deployed in real time for business intelligence applications to provide actionable insights for decision-making. Time series forecasting is essential in areas like finance, manufacturing, and supply chain management that use past data to anticipate trends. SAS Enterprise Miner can develop complex time series models to predict future values from previous data. These models analyse data patterns, seasonality, and cycles to assist company's plan. SAS Enterprise Miner supports ARIMA, Exponential Smoothing, and State Space Models for time series forecasting. Forecasting time-stamped data like sales or stock prices using these methodologies informs decision-making. Retailers may better manage inventory by using time series forecasting to estimate product demand throughout the year. SAS Enterprise Miner's time series models can scale for companies with plenty of historical data since it can handle enormous datasets. Automated model selection and validation let firms pick the optimum forecasting model with least effort, improving operational efficiency and accuracy.

Figure 5 overview diagram shows SAS Enterprise Miner's business intelligence pipeline. Integrating relational databases, flat files, and cloud storage starts it. Data preprocessing—cleansing, transformation, and feature selection—is essential for data quality. SAS Enterprise Miner trains decision trees, neural networks, and regression models.

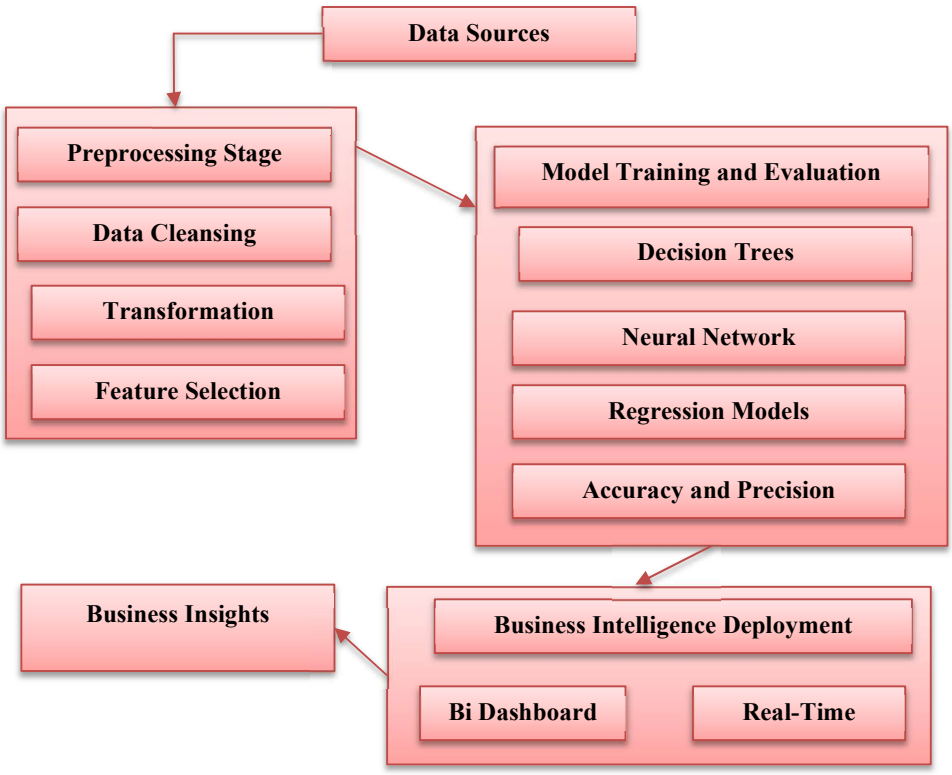

Figure 5. Data Flow Diagram for Utilizing SAS Enterprise Miner in Business Intelligence

Fraud detection is a major issue in banking and insurance. SAS Enterprise Miner uses machine learning to identify and prevent fraud. Its anomaly detection, classification models, and network analysis capabilities make it a complete fraud detection platform. Machine learning algorithms are trained on prior fraudulent and valid transactions to create fraud detection models. After learning fraud characteristics, the model may identify questionable activity in real data. Organizations may identify fraud in real time, reducing losses and boosting security. Large-scale data processing improves SAS Enterprise Miner's fraud detection. Scalability is crucial when analysing millions of transactions every day. Automating fraud detection reduces financial risk and boosts client confidence via security.

RESULTS AND DISCUSSION

Manufacturing, where equipment failure may cause downtime and financial losses, requires predictive maintenance. SAS Enterprise Miner helps enterprises forecast equipment and system failures with advanced predictive maintenance models. These algorithms analyse previous performance data to identify maintenance needs before breakdowns. Decision trees, random forests, and support vector machines are supported for predictive maintenance on the platform. These algorithms find failure patterns in sensor data, operating records, and equipment use. These patterns help forecast malfunctions and improve maintenance programs. With predictive maintenance models, firms may decrease downtime, prolong equipment life, and save expenses. SAS Enterprise Miner's interaction with other SAS products makes predictive maintenance models easy to incorporate into asset management processes, enhancing operational efficiency. Figure 6 shows an SAS Enterprise Miner-analysed dataset with five characteristics. Each component represents business intelligence KPIs including sales, customer interaction, operational efficiency, marketing efficacy, and product returns. Observations from various time periods or business divisions indicate how these indicators change. The colour intensity shows each metric's value, helping visualise performance across data. This research uses data visualisation to discover patterns, improvement possibilities, and strategic planning prospects for firms.

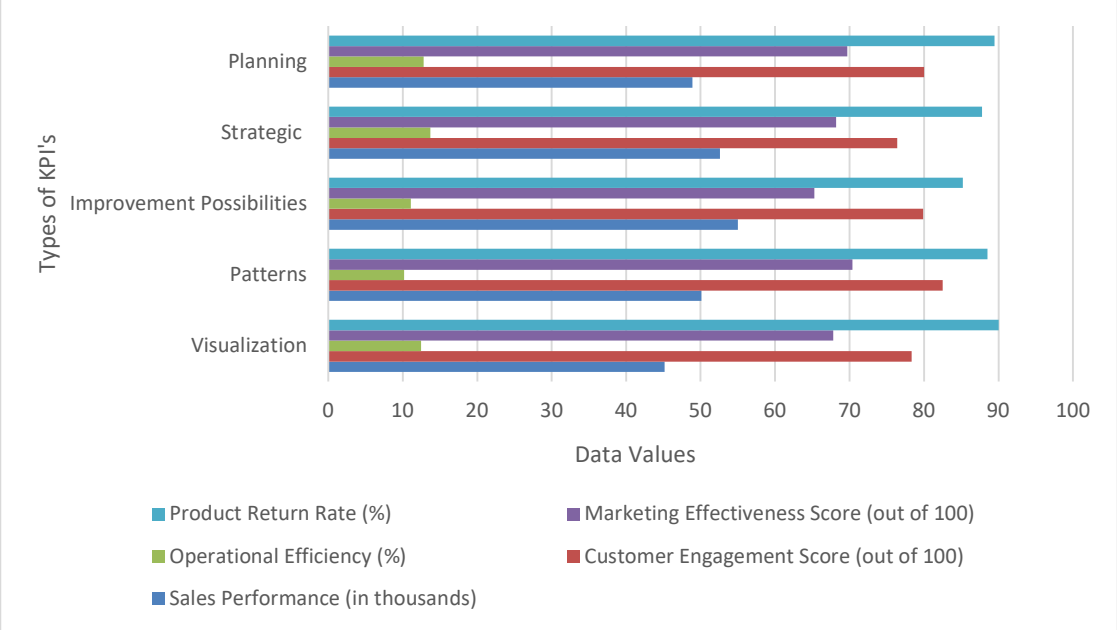

Figure 6. Sample Data for Business Intelligence Applications

Table 1 describes essential Rattle data pretreatment methods for dataset analysis. It involves data cleansing, transformation, feature selection, normalization, and missing values. The user-friendly Rattle interface includes the Clean Data button for mistake correction, the Transform tab for data format changes, and options for imputing missing values. Each assignment organizes data for accurate model training. Eliminating duplication, numericizing factors, and standardizing income data are examples. The chart also lists advantages like enhanced model performance and full datasets and drawbacks like data loss or bias during imputation. This overview shows

how Rattle's easy-to-use preprocessing tools allow users of all skill levels to maintain good data quality, making data mining more efficient and successful in generating insights.

Table I. Data Preprocessing Techniques in Rattle for Data Mining

Task	Data Cleaning	Data Transformation	Feature Selection	Data Normalization	Handling Missing Values
Objective	Remove noise and correct errors	Convert data formats for compatibility	Select relevant attributes for modelling	Scale data for improved performance	Address incomplete data points
Rattle Tool	Clean Data Button	Transform Tab	Importance Tab	Normalize Option	Impute Missing Values
Example Application	Remove duplicate entries	Convert factors to numerical values	Select demographic factors for analysis	Standardized income data	Impute missing ages
Benefits	Ensures high-quality input	Adapts data for various models	Focus on key variables	Improves model convergence	Provides complete datasets
Challenges	Time-consuming for large data	Potential loss of information	Risk of excluding useful features	Can alter data distributions	Risk of bias in imputation

Retailers must understand consumer behaviour and optimize inventory management to succeed in a competitive economy. SAS Enterprise Miner lets retailers examine massive transaction data, consumer interactions, and market trends. Retailers use this data to optimize pricing, customer segmentation, and supply chain management. Because SAS Enterprise Miner can handle big datasets, merchants may analyse sales data at a granular level to find patterns and trends that standard analytics tools may overlook. For instance, clustering algorithms may group clients by purchase behaviour for tailored marketing. Predictive algorithms may also help retailers improve inventory levels by predicting product demand. Retail analytics using SAS Enterprise Miner improves decision-making, customer happiness, and profitability. Scalability and integration with other retail systems make the platform important for current retail operations. Figure 7 shows another example dataset demonstrating SAS Enterprise Miner's sophisticated data mining methods. Like the previous, this dataset contains five attributes that may reflect consumer demographics, purchasing behaviour, product ratings, service reviews, and return rates. The structure of observations allows researchers to find hidden patterns and correlations in consumer interactions across time. The visualisation shows dataset variances, helping stakeholders make educated choices to improve customer experience and operational procedures. SAS Enterprise Miner simplifies these analytics for superior business information and actionable insights.

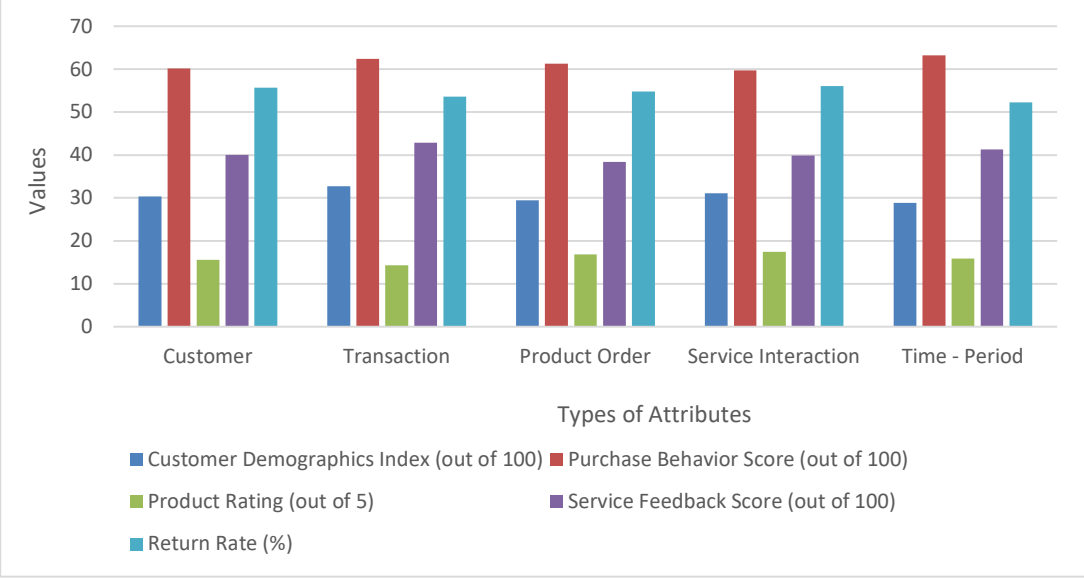

Figure 7. Sample Data for Advanced Data Mining

Table 2 shows how Rattle data visualization tools improve dataset knowledge during mining. It includes histograms, box plots, scatter plots, correlation matrices, and decision tree diagrams. Histograms and scatter plots assist with analyzing distribution patterns and variable relationships. Rattle's Explore tab and correlation matrices, and decision tree visualizations help users understand data patterns. To discover outliers or simplify complicated categorization findings, use box plots or decision tree diagrams. The table shows how visualizations may simplify distribution interpretation and decision routes, as well as their drawbacks, such as big dataset complexity. This table shows how Rattle's visualization features simplify data analysis and help users find patterns and insights.

Financial organizations struggle to manage credit risk. SAS Enterprise Miner lets banks and lenders construct and optimize credit risk models to predict default and make smart lending choices. Credit scores, transaction history, and income levels are used to forecast new application default in these models. Credit risk modelling methods including logistic regression, gradient boosting, and neural networks are supported by the platform. These algorithms help banks identify high-risk borrowers and adapt lending tactics. SAS Enterprise Miner's model validation ensures credit risk models are correct and generalize well to new data. Advanced credit risk analytics may decrease defaults, losses, and portfolio performance for financial organizations. SAS Enterprise Miner's connection with other financial systems enables real-time risk monitoring, improving the institution's response to developing issues.

TABLE II. Data Visualization Technologies in Rattle

Technique	**Histograms**	**Box Plots**	**Correlation Matrices**	**Decision Tree Diagrams**
Description	Visualizes data distribution	Displays data spread and outliers	Identifies correlations between features	Visualizes decision paths
Rattle Tool	Explore Tab	Explore Tab	Correlation Matrix Tab	Tree Tab
Use Case	Understand sales data spread	Analyze income distribution by gender	Examine feature correlations in predictions	Visualize customer segmentation decisions
Benefits	Easy interpretation of distributions	Identify outliers effectively	Shows feature relationships	Simplifies complex decision-making paths
Challenges	Hard to interpret with large datasets	Sensitive to extreme values	Overly complex with many variables	Can become cluttered with deep trees

Data helps marketing departments design successful campaigns that connect with their target demographic. SAS Enterprise Miner helps companies evaluate consumer data and improve campaign strategy with strong marketing analytics solutions. Marketers may anticipate campaign performance and spend resources more effectively by constructing predictive models using historical campaign data. SAS Enterprise Miner provides regression analysis and decision trees to uncover consumer behaviour drivers. Our algorithms can forecast consumer reactions to certain marketing activities, allowing more tailored and targeted campaigns. SAS Enterprise Miner propensity models may help marketers target high-value prospects by identifying probable convertors. The platform's capacity to handle huge consumer data means marketing analytics can expand as firms develop. Its reporting and visualization feature also make it easier to share data with stakeholders, strengthening marketing strategy.

CONCLUSION

This research illustrates the use of sophisticated data mining methodologies using SAS Enterprise Miner to obtain significant insights for business intelligence. The framework facilitates a systematic assessment of consumer patterns and behavioural trends by examining factors related to customers, including demographic index, buying behaviour score, product rating, service feedback score, and return rate. Every data record is regarded as an independent observation, enabling the model to discern correlations between client attributes and company results. The implementation demonstrates that systematic preprocessing, model training, and validation enhance reliable prediction performance. The findings validate that advanced data mining techniques can efficiently identify significant factors affecting consumer satisfaction and repurchase behaviour. These insights facilitate data-driven decision-making and strategic planning in competitive corporate contexts. The research also demonstrates the significance of combining analytical tools with structured information to improve operational efficiency and customer relationship management. Future research may investigate more extensive datasets, supplementary predictive factors, and hybrid modelling techniques to enhance business intelligence capabilities and optimize organizational performance.

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