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A Multi-Algorithmic Method for Ranking B2B Order Success Factors in an ERP Environment

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Abstract. Predicting order success in business-to-business environments remains challenging due to the multifactorial complexity of transactions and limitations in traditional forecasting. This study develops a multi-algorithmic method to identify and rank factors influencing order success, with empirical validation in an ERP-based transactional environment. It integrates five feature significance scorers (Area Under the Curve, Mutual Information, distance correlation, Logistic Regression, and Decision Trees) with modified Borda rank aggregation. Analysis of 86,794 orders spanning 2017–2025, with 25 characteristics, revealed that communication factors, particularly message count, demonstrate the strongest influence on success. Historical cooperation experience ranks second, while financial parameters showed ambiguous results, and discounts proved insignificant. Order flexibility positively correlates with success, whereas temporal characteristics showed no influence. The study contributes a methodologically justified five-scorer selection, a modified Borda aggregation method for consolidated scale-independent factor ranking, and a reproducible pipeline for structured transactional data.

Keywords: B2B order prediction; feature ranking; multi-algorithmic analysis; ERP systems; machine learning; rank aggregation; communication factors; order success; decision-making system

1. Introduction

In today's digital economy, accurate forecasting of business transaction outcomes is critical for organizational success and competitiveness. Companies worldwide invest billions in enterprise resource planning (ERP) systems – integrated software platforms that manage core business processes – yet many struggle to predict which orders will succeed or fail. This challenge is particularly acute in business-to-business (B2B) environments, where transactions involve complex negotiations, longer sales cycles, and multiple decision-makers. Understanding the factors that determine order success can help organizations optimize resource allocation, improve customer relationships, and enhance overall operational efficiency.

Despite widespread ERP adoption for process automation, current procedures for predicting order outcomes remain limited. Classical statistical models often fail to capture the multifactorial nature of B2B transactions, where success depends on numerous interconnected factors, including product characteristics, customer history, market conditions, and resource availability. While modern machine-learning techniques mitigate some of these limitations, they have not yet been combined with rigorous, scorer-neutral procedures for identifying and ranking the underlying success factors – a prerequisite for transparent, decision-support-oriented prediction in ERP environments. A detailed review of prior work on these topics is provided in Section 2.
On this basis, the present study addresses three specific research and development problems that, to the best of our knowledge, are not jointly resolved by existing studies on B2B order success prediction.

P1. Existing feature-importance procedures in this domain typically rely on a single method, whose internal assumptions (linearity, distributional form, capacity to model interactions) systematically bias the resulting ranking; no scorer-neutral aggregation has been established for B2B order success factors.

P2. When several feature significance scorers are applied to the same dataset, their rankings often diverge, and there is no formally specified rule that reconciles such divergence into a single, interpretable ordering whose properties – methodological neutrality, scale invariance, robustness to outliers in individual scorer outputs, interpretational clarity – can be argued for explicitly.

P3. Even when individual scorers are reported in the literature, the corresponding processing pipelines are rarely described at a level of detail that allows independent reproduction in structured transactional settings, including but not limited to ERP-derived data, which limits the operational integration of such results into decision-support modules.

Building on this foundation, we previously developed an enhanced forecasting module for the Odoo ERP platform (Miroshnychenko, 2024) that incorporates additional contextual factors when predicting order quantities. This development creates new requirements for understanding which factors most significantly influence success and how they should be weighted in prediction models, which is essential for creating effective computer-integrated decision support systems that can guide managers in resource allocation and order management.

Our previous studies established foundational insights into B2B order success prediction. A statistical analysis approach (Miroshnychenko and Vovna, 2025) identified communication factors and partner success metrics as dominant predictors using parametric and non-parametric tests with automatic method selection. Subsequently, automated feature selection research (Miroshnychenko et al., 2025) demonstrated the stability of key predictive features across six different selection methods combined with XGBoost hyperparameter optimization. The present work complements these earlier results by introducing a unified ranking method that consolidates multiple, heterogeneous feature significance scorers into a single, interpretable ordering.

The aim of this study is to rank factors influencing B2B order success through a multi-algorithmic feature significance method. We address the research question: which order characteristics have the greatest impact on completion probability, and how should their relative importance be quantified in a methodologically neutral way? To address problems P1–P3, this study makes the following contributions:

C1. The selection and methodological justification of five mathematically distinct feature significance scorers – Area Under the Curve (AUC) for univariate discrimination, Mutual Information (MI) for information-theoretic dependence, distance correlation (dCor) for scale-invariant nonlinear relationships, Logistic Regression (LogReg) for multivariate linear effects, and Decision Trees (DecTree) for interaction discovery – that capture complementary forms of dependence between predictors and a binary outcome.

C2. A modified Borda rank-aggregation method in which heterogeneous scorer-specific outputs are transformed into ranks and the consolidated rank is computed as the arithmetic mean of scorer-specific ranks rather than as the classical sum of positions; this rule is methodologically neutral, scale-invariant, robust to outliers in individual scorer outputs, and interpretationally clearer than the classical formulation.

C3. A reproducible end-to-end pipeline that operationalizes the proposed method – from raw structured transactional data through type-specific preprocessing (cyclical encoding of temporal variables, OHE Extended Compact encoding of categorical variables, robust scaling of numerical variables) and scorer-specific feature ranking to rank aggregation – and can be applied to other structured datasets and decision-support contexts. The empirical results obtained from 86,794 ERP-based B2B order records over 2017–2025 are reported throughout this paper as an illustrative application of the proposed method to a single Odoo dataset rather than as a generalizable taxonomy of B2B success factors.

2. Related work

Recent studies demonstrate that machine learning (ML) algorithms and artificial intelligence can significantly enhance forecasting performance in sales processes (Hrischev and Shakev, 2023; Lin et al., 2023; Zoltners et al., 2021). For example, random forest models have achieved prediction accuracy with R^2 values approaching 0.94 (where 1.0 represents perfect prediction) in ERP environments (Bauskar, 2024), while supervised ML techniques in B2B analytics have shown 2.5-fold improvements over traditional models (Rohaan et al., 2022). These advances suggest that data-driven techniques can accommodate the complexity inherent in modern business transactions more effectively than purely statistical baselines (Bauskar, 2024).

However, opinions remain divided among researchers regarding the most effective way to predict order success. Some authors advocate for increasingly sophisticated ML algorithms to capture non-linear relationships and feature interactions (Rohaan et al., 2022; Miroshnychenko et al., 2024), while others emphasize the importance of domain knowledge and interpretable models that business users can understand and trust (Bauskar, 2024; Lin et al., 2023). Existing methods further face several unresolved challenges: limited adaptability to rapidly changing market conditions, inadequate accounting for interdependencies among order characteristics, and insufficient incorporation of business-specific factors such as component availability or the status of pending approvals (Miroshnychenko et al., 2024). These limitations highlight a critical gap between technological capability and practical business requirements.

Several studies have attempted to identify success factors for B2B processes using diverse analytical frameworks. Research has explored organizational characteristics associated with effectiveness (Eid et al., 2002), developed conceptual models for digitalization success (Zoltners et al., 2021), and investigated factors influencing specific business outcomes (Lin et al., 2023; Wilson and Stephens, 2023; Günther, 2021; Høgevold et al., 2022; Rodriguez et al., 2022). However, these works predominantly examine factors in isolation rather than comprehensively evaluating their relative importance or combined effects on order success, which limits the practical application and automated integration of these findings into decision-support systems.

Rank-aggregation methods offer a complementary direction. They enable the reconciliation of multiple rankings derived from different evaluation criteria, providing a structured way to synthesize results from heterogeneous analytical methods. Such methods have demonstrated effectiveness across diverse research domains, including web search (Dwork et al., 2001), bioinformatics (Wald et al., 2012; Sarkar et al., 2014), and environmental decision-making (Vambol et al., 2023), suggesting their suitability for B2B order success ranking. The present study builds on this line of work by introducing a modified Borda rule based on the arithmetic mean of ranks rather than the classical sum of positions, as detailed in Section 3.

3. Materials and methods

The proposed method for a comprehensive analysis of factors (features) influencing a binary success outcome in structured transactional data integrates feature significance scorers from different areas of statistical analysis and machine learning, consolidated through a single rank-aggregation rule. In this study, the method is empirically instantiated for B2B order success using ERP-derived transactional records. The method comprises three sequential stages: type-specific data preprocessing, per-scorer feature significance assessment, and modified Borda rank aggregation.

The initial dataset for the period from July 2017 to January 2025 consists of 86,794 records containing order information, with 25 characteristics (features): 20 numerical (11 floating-point, 9 integer) and 5 categorical (object)[1]. For clarity of interpretation, the substantive meaning, category, data type, and measurement scale of the original analytical features are summarized in Appendix A.

Figures 1–5 present univariate visualizations of the original transaction records using violin plots, directly associating class distributions with quantitative values. These plots illustrate the probability density of representative raw variables across the major feature categories prior to preprocessing, augmented with precise median markers and interquartile ranges to provide immediate quantitative insight into the central tendency and dispersion of each outcome for both successful and unsuccessful orders.

Figure 1 illustrates the distribution of customer relationship duration. For successful orders, the density is characterized by a median of 894.0 days (mean: 1016.5, standard deviation [SD]: 782.7), with an interquartile range (IQR) from 343.0 to 1632.0 days. For unsuccessful orders, the density concentrates around a median of 734.0 days (mean: 838.2, SD: 738.4), with an IQR spanning from 147.0 to 1,335.0 days.

[1] https://github.com/serhii-miroshnychenko-mariupol/PublicData/blob/main/dataset-1.csv

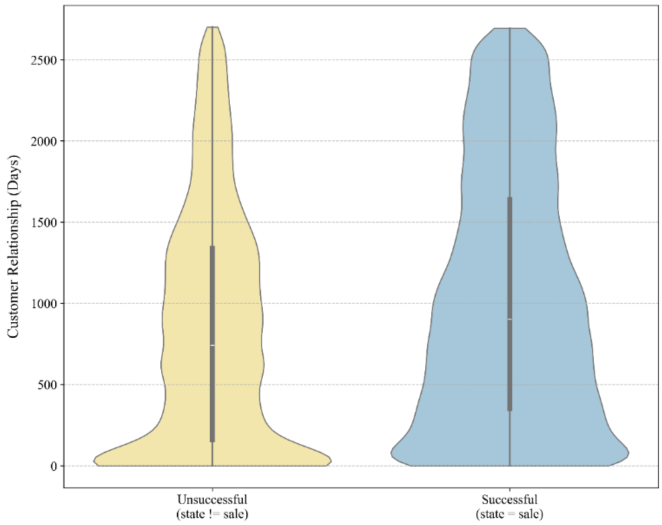

Figure 1. Order success as a function of customer relationship duration (customer_relationship_days)

Figure 2 visualizes the temporal distribution of orders by their creation date. The probability density for successful transactions peaks around a median date of February 23, 2021 (mean: March 30, 2021), bounded by an IQR from May 21, 2019, to March 2, 2023. Correspondingly, the unsuccessful transactions display a density distribution with a median of November 20, 2020 (mean: January 15, 2021) and an IQR spanning from September 18, 2019, to May 4, 2022.

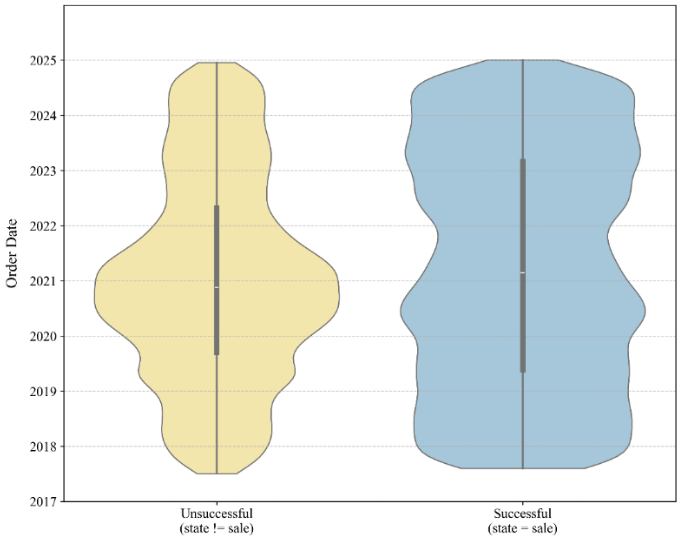

Figure 2. Order success over time by order date (date_order)

Figure 3 displays the distribution of the prior transaction history, presented on a logarithmic scale (log10) to accommodate high-frequency outliers while preserving resolution for smaller values. Successful conversions exhibit a median of 23.0 previous orders (mean: 70.04, SD: 137.7, IQR: 5.0–72.0). Conversely, the unsuccessful orders demonstrate a median of 9.0 (mean: 39.73, SD: 78.91, IQR: 1.0–42.0).

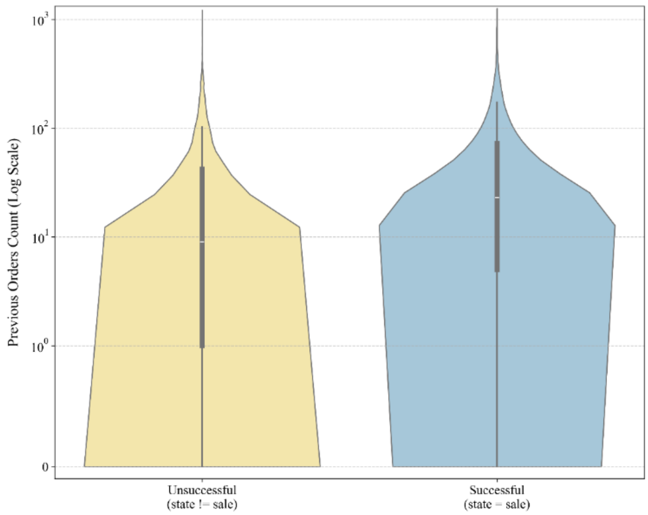

Figure 3. Order success as a function of prior transaction history (previous_orders_count)

Figure 4 details the intraday distribution of order placement times. The density curves for both classes share an identical median of 11:00 AM. For successful orders, the mean is 10.79 with a standard deviation of 2.83 and an IQR from 08:00 to 13:00. Unsuccessful orders show a mean of 11.18 (SD: 2.97) and an IQR extending from 09:00 to 14:00.

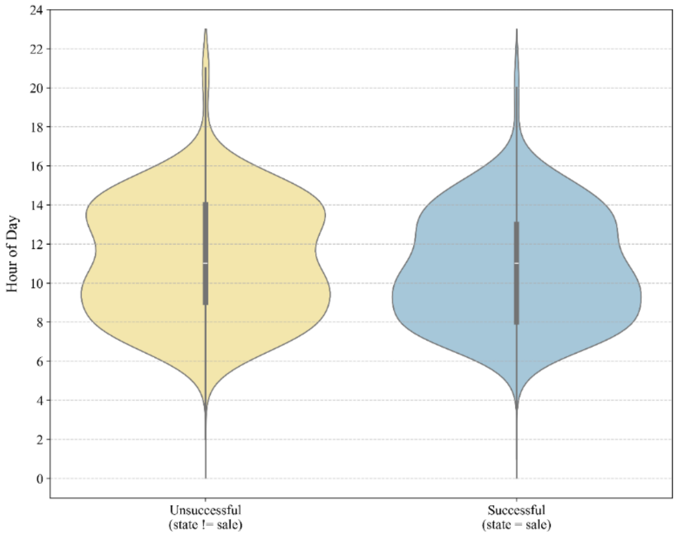

Figure 4. Order Success as a Function of Order Placement Time (hour_of_day)

Figure 5 visualizes the density distribution of communication intensity, utilizing a logarithmic scale due to a heavily right-skewed distribution. Successful interactions indicate a broader spread toward higher values with a median of 8.0 messages (mean: 10.81, SD: 8.97, IQR: 6.0–12.0). In contrast, the unsuccessful orders are characterized by a denser concentration around lower values, showing a median of 5.0 messages (mean: 6.03, SD: 5.39, IQR: 4.0–7.0).

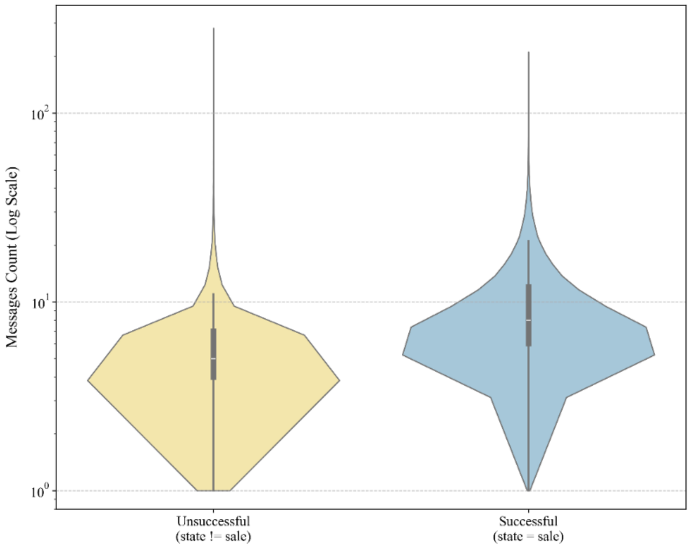

Figure 5. Order success as a function of communication intensity (messages_count)

The target variable is the binary indicator of order success – ‘is_successful’. If an order was approved and successfully completed, the target variable equals 1; otherwise, for unapproved or canceled orders for any reason, ‘is_successful’ equals 0. Initial analysis of the target variable distribution revealed class imbalance – approximately 63% of orders are successful, which should be considered in subsequent modeling. Preliminary analysis indicated significant variance and extreme values in numerical features, especially order amounts and partner history characteristics. The set of potential predictors (features) is formed based on order and customer characteristics. Features that either contained no predictive information or caused direct target leakage were removed from the analyzed dataset.

An important aspect of data preparation is processing temporal characteristics. The ‘create_date’ variable, reflecting the order creation date and time, was transformed to extract temporal components to identify possible temporal dependencies. We extracted the following characteristics: day of week, month, quarter, and hour of day when the order was placed. This transformation allows identification of potential seasonal fluctuations and cyclicality in order placement processes. For cyclical temporal features such as ‘day_of_week’, ‘month’, and ‘hour_of_day’, we applied cyclical encoding using sinusoidal and cosine transformations (Chakraborty and Elzarka, 2018), ensuring the correct representation of temporal cycles in the multidimensional feature space. This transformation was implemented using the feature_engine library[2], providing standardized and efficient conversion of cyclical variables. Based on ‘create_date’, we also created the ‘create_date_months’ parameter, whose value represents the temporal distance of a specific order's creation moment from the initial observation point, measured in months, where the date of the first recorded system order serves as the starting point. This transformation allows the time series to be represented as a monotonically increasing numerical sequence reflecting the temporal distance between orders in months. The ‘create_date_months’ variable can be used as a regressor in ML models to account for temporal dependencies and evolution of order characteristics over time. Additionally, this variable enables analysis of order success dynamics over time, which may reveal the influence of seasonality and long-term trends.

Categorical variables such as ‘salesperson’ (responsible for sales) and ‘source’ (order source) require special processing for integration into mathematical models. Analysis of unique values revealed moderate cardinality for the ‘salesperson’ variable and somewhat higher cardinality for ‘source’, with 31 and 66 unique values, respectively. For these categorical variables, we applied the OHE Extended Compact encoding method, implemented according to (Ul Haq et al., 2019). This method avoids creating false ordinal relationships between categories while compressing sparse data, helping prevent excessive dataset expansion.

Since the numerical variables in the dataset exhibit significant scale variability and contain extreme values (outliers), they require appropriate processing and scaling. Specifically, statistical tests determined that variables such as ‘order_amount’, ‘partner_total_orders’ (total number of partner orders), ‘partner_avg_amount’ (average partner order amount) have wide value ranges and asymmetric distributions. For

[2] https://feature-engine.trainindata.com/en/1.8.x/user_guide/creation/CyclicalFeatures.html

normalizing numerical variables, we applied the Robust Scaler method[3], which, by using median and interquartile range for centering and scaling data, significantly reduces the influence of extreme values on scaling results, which is particularly important for variables with pronounced distribution asymmetry, as in the case of 'order_amount'. To detect outliers in numerical variables, we used the interquartile range method (Dekking et al., 2005) – a robust statistical technique that identifies outliers based on their distance from the distribution quartiles. Outlier analysis using this method revealed a significant number of extreme values in variables such as 'order_amount', 'partner_avg_amount', 'partner_success_avg_amount' (average amount of successful customer orders), and 'order_lines_count' (number of items in order). Given the potential information these outliers may provide for predicting order success, we decided to apply the above-described robust scaling techniques to minimize their impact on the model.

Following preprocessing (see Fig. 6), we obtained the final analytical dataset for subsequent modeling. The preprocessing procedures used correspond to the specificity of the analyzed dataset and requirements for subsequent modeling, particularly accounting for the presence of cyclical variables, categorical features with moderate cardinality, and the presence of extreme values in numerical variables. This produced a consistent analytical feature matrix for subsequent feature significance assessment.

An important feature of this study is the need to assess significance for both numerical and categorical features after their respective encoding. The selected set of scorers enables comprehensive analysis of B2B order data from multiple perspectives, ranging from univariate statistical analysis to complex ML models that account for feature interactions. All five scorers are distribution-free or robust to distributional assumptions, which is critically important for analyzing real B2B business data that often deviate from theoretical distributions. The selected scorers also work effectively with both numerical and categorical variables after proper encoding, allowing full analysis of heterogeneous data.

The stages shown in Fig. 6 are operationalized as follows.

Stage I (Feature engineering and removal of irrelevant variables). Prior to the statistical analysis, raw records exported from the Odoo PostgreSQL backend are transformed into an analytical dataset with 25 features. This stage removes three categories of variables: (a) technical identifiers that could enable memorization rather than generalization ('id', 'order_id', 'partner_id', 'customer_id'); (b) low-predictive-value B2B attributes whose distributions in the analyzed environment are dominated by a single modality or are operationally redundant ('sales_team', 'customer_category', 'customer_country', 'product_categories', 'payment_term', 'delivery_method'); and (c) post-event target-leakage variables, most notably processing_time_hours, whose values become available only after the order has been completed and would therefore be unavailable at prediction time. All intermediate columns used exclusively for the computation of historical aggregates are also discarded. In addition, historical partner-level aggregates ('partner_*') are constructed under a temporal leakage prevention rule: when a feature such as 'partner_success_rate' or 'partner_avg_amount' is computed for a given order, the contribution of that same order is subtracted from the cumulative sum, so that only information available before order creation is used. Finally, a near-zero-variance filter is applied at a 95% majority-value threshold: features in which more than 95% of

[3] https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.RobustScaler.html

observations share an identical value after the cleaning steps above are treated as non-informative and are excluded from the analytical dataset.

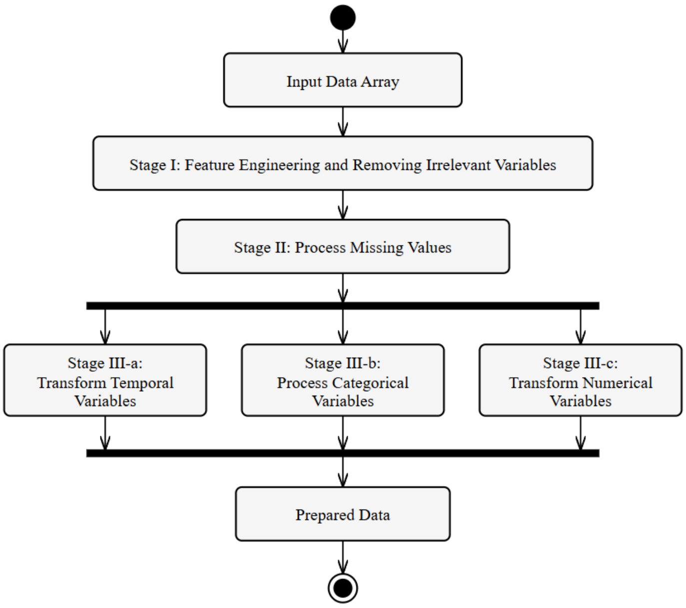

Figure 6. Data Preprocessing Workflow Diagram

Stage II (Processing of missing values). Missing values in numerical variables are imputed by the column median, and in categorical variables by the column mode (majority value); these strategies are robust to the asymmetric distributions and class imbalance present in the analyzed dataset and avoid introducing artificial trends.

Stage III-a (Transformation of temporal variables). From the raw 'create_date' variable we extract the components 'day_of_week', 'month', 'quarter', and 'hour_of_day', as well as the monotonic distance feature 'create_date_months' (months elapsed since the first recorded order). The cyclical components are subsequently encoded by sinusoidal and cosine projections via the CyclicalFeatures transformer of the feature_engine library[2] (Chakraborty and Elzarka, 2018). After the extraction of these components, the original 'create_date' column is itself discarded from the analytical feature matrix.

Stage III-b (Processing of categorical variables). The categorical variables 'salesperson' (31 unique values) and 'source' (66 unique values) are encoded by the OHE Extended Compact (OHE-EC) procedure of (Ul Haq et al., 2019), which transforms each categorical attribute with d distinct values into d+1 indicator attributes (the additional attribute reserves capacity for previously unseen values, which is appropriate for 'source' whose value space evolves over time) and then applies sparsity-aware compaction by retaining only non-zero indicators together with their feature index. We use the High Distribution First (HDF) variant, in which indicator attributes are ordered by descending value distribution; the implementation follows the original specification (Ul Haq et al., 2019), as no public package was available at the time of analysis.

Stage III-c (Transformation of numerical variables). Seventeen numerical variables (‘order_amount’, ‘order_messages’, ‘order_changes’, ‘partner_total_orders’, ‘partner_order_age_days’, ‘partner_avg_amount’, ‘partner_success_avg_amount’, ‘partner_fail_avg_amount’, ‘partner_total_messages’, ‘partner_success_avg_messages’, ‘partner_fail_avg_messages’, ‘partner_avg_changes’, ‘partner_success_avg_changes’, ‘partner_fail_avg_changes’, ‘order_lines_count’, ‘discount_total’, ‘create_date_months’) are scaled with RobustScaler from scikit-learn[3], which centers each variable on its median and scales by its interquartile range, ensuring resistance to outliers identified via the IQR rule (Dekking et al., 2005).

The outputs of Stages III-a, III-b, and III-c are merged column-wise within the same row index of the order-level table, producing the analytical feature matrix (“Prepared data”) used as the common input to all five feature significance scorers.

In the context of feature significance assessment, the Area Under the Curve (AUC) scorer, based on evaluating the area under the ROC curve (Fawcett, 2006), is used to assess an individual feature's ability to separate positive and negative classes (successful and unsuccessful orders). Mathematically, AUC is the probability that a randomly selected observation from the positive class has a higher predicted rank than a randomly selected observation from the negative class (Calders and Jaroszewicz, 2007). We chose the AUC scorer for assessing feature significance because it is effective with binary target variables, insensitive to feature scaling, and able to evaluate monotonic relationships between features and target variables. The method's advantage is that it requires no assumptions about data distribution and works effectively with both numerical and categorical features after encoding. In this study, we used the AUC implementation in the sklearn library, specifically the roc_auc_score function, to identify features that best separate successful and unsuccessful orders, without considering complex feature interactions.

To identify non-obvious patterns between order attributes and customer interaction effectiveness, we calculated the MI indicator, which measures the amount of information that one random variable X provides about another variable Y. In the context of feature selection tasks, MI is used as a criterion for evaluating feature significance based on their ability to reduce uncertainty about the target variable. In practice, particularly in the Python scikit-learn library, MI for classification is implemented using the mutual_info_classif function, which supports both numerical and discrete features. Computation is based on non-parametric entropy estimates, with noise added to continuous variables to avoid artifacts caused by repeated values (Kraskov et al., 2004). Thus, automatic processing of mixed feature types is available, as well as parallel computation across features[4]. One of the main advantages of MI over correlation coefficients is its ability to capture both linear and complex nonlinear dependencies (Ross, 2014). This property makes MI an effective tool in cases where complex relationships are expected, such as in B2B order effectiveness prediction tasks, thereby enabling more accurate decision-making models.

In this study's context, to identify features with any statistical relationship with order success, we applied the dCor scorer using the dcor library[5] as a complement to other

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[4] https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.mutual_info_classif.html

[5] https://dcor.readthedocs.io/en/stable/functions/dcor.distance_correlation.html

applied scorers that might miss certain types of dependencies. dCor is a statistical measure that evaluates the degree of dependence between two random vectors and can identify both linear and nonlinear dependencies, making it a powerful tool for analyzing complex data. A key property of the method is that dCor equals zero if and only if variables are statistically independent, thus providing a reliable independence test (Székely et al., 2007).

To analyze order success based on modeling binary outcome probabilities, we applied LogReg, which allows determining event probability as a function of a set of independent variables (Kleinbaum and Klein, 2010; Lee, 2025). This method allows assessment of both the strength and direction of each feature's influence on success probability, and provides statistical significance tests for this influence that account for the simultaneous influence of all features. In data processing for this study, we used the LogisticRegression class from the sklearn library[6] to obtain interpretable results and more reliable significance estimates for binary target variables compared to methods developed for continuous variables.

To account for nonlinear interactions between features and identify the most discriminative ones, we applied DecTree – a non-parametric ML method that creates prediction models by learning decision rules derived from studied data (Breiman et al., 2017). Unlike statistical methods that evaluate each feature separately, DecTree considers features in the context of their interaction, which is particularly important for complex business data. This scorer requires no assumptions about data distribution and performs equally well across different feature types, meeting the requirements of this study. In the practical context of B2B order analysis, applying DecisionTreeClassifier from the sklearn library[7] enables the identification of key factors influencing order success and the specification of specific threshold values for these factors, thereby enhancing the practical value of the analysis results.

The mathematical diversity of applied scorers ensures independent data analysis by each method, creating a kind of "cross-validation" system for results that minimizes the risk of identifying false patterns and increases confidence in features identified as significant. Thus, using these five scorers enables comprehensive analysis of feature significance, avoids the limitations inherent to individual scorers, and provides a reliable foundation for subsequent predictive model development and business decision-making.

In the context of comprehensive feature significance analysis for predicting B2B order success using multiple heterogeneous scorers, a methodological challenge arises: integrating the obtained results. The adopted approach is based on the rank aggregation concept (Dwork et al., 2001), which allows reconciling results from scorers that potentially use different scales and evaluation principles.

Let $F = \{f_1, f_2, \dots, f_n\}$ be the set of studied features, and $M = \{m_1, m_2, \dots, m_k\}$ be the set of significance evaluation scorers, where in this study $k = 5$ (AUC, MI, dCor, LogReg, DecTree). Each scorer m_j assigns feature f_i a certain significance value $S_j(f_i)$, which reflects the degree of this feature's influence on the target variable according to scorer m_j's mathematical apparatus. To ensure comparability of results from different scorers, we implement a transformation to a rank scale. The rank of feature f_i by scorer m_j is defined by Eq. (1):

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[6] https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
[7] https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html

$$R_j(f_i) = |\{f_l \in F | S_j(f_l) \geq S_j(f_i)\}|, \tag{1}$$

where f_i is the feature for which rank is calculated; F is the complete set of all studied features; f_l is any feature from set F that serves as a variable in comparison; $S_j(f_i)$ is the significance value that scorer m_j assigns to feature f_i; $S_j(f_l) \geq S_j(f_i)$ is the condition that feature f_l's significance is not less than feature f_i's significance; $\{f_l \in F | S_j(f_l) \geq S_j(f_i)\}$ is the set of all features whose significance is not less than feature f_i's significance; $|\cdot|$ is set cardinality, i.e., the number of elements satisfying condition $S_j(f_l) \geq S_j(f_i)$.

In contrast to the classical Borda method (Dwork et al., 2001), which aggregates complete rankings through a sum-of-positions logic, the proposed modification applies the arithmetic mean of the scorer-specific ranks:

$$\bar{R}(f_i) = \frac{1}{k} \sum_{j=1}^{k} R_j\,(f_i). \tag{2}$$

where $R_j(f_i)$ is the rank of feature f_i assigned by scorer m_j according to Eq. (1), k is the number of scorers used in the aggregation, and $\bar{R}(f_i)$ is the resulting mean rank of feature f_i. In this study, $k = 5$, corresponding to AUC, MI, dCor, LogReg, and DecTree.

This integral indicator $\bar{R}(f_i)$ serves as a generalized measure of feature f_i significance, considering results from all involved scorers. A lower value of $\bar{R}(f_i)$ indicates higher consolidated feature significance. The consolidated ordering is obtained by applying Eq. (1) to each (feature, scorer) pair and then aggregating the resulting per-method ranks via Eq. (2).

The proposed modification to the Borda method has several methodological advantages. First, the rule is methodologically neutral, giving no preference to any scorer and treating each as an equal contributor to the final assessment, thereby minimizing methodological biases. Second, it is invariant with respect to measurement scales, as rank transformation eliminates the problem of incomparable scales from different scorers. Third, it is robust, since the use of ranks instead of absolute values reduces sensitivity to outliers and extreme values in individual scorer outputs. Fourth, it offers interpretational clarity, as the mean rank has a clear interpretation as the feature's averaged position in the significance-ordered list. Within the overall workflow shown in Fig. 7, the modified Borda stage is used to calculate the mean rank for consolidated feature ordering.

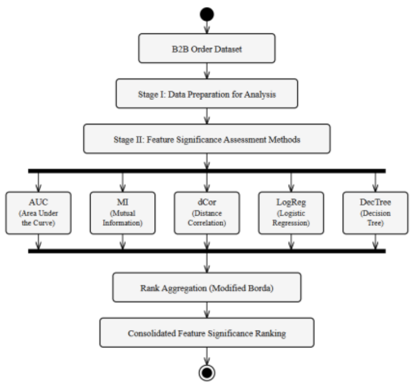

Figure 7. Flowchart of the feature significance assessment process

The proposed modification to the Borda method has several methodological advantages. First, the rule is methodologically neutral, giving no preference to any scorer and treating each as an equal contributor to the final assessment, thereby minimizing methodological biases. Second, it is invariant with respect to measurement scales, as rank transformation eliminates the problem of incomparable scales from different scorers. Third, it is robust, since the use of ranks instead of absolute values reduces sensitivity to outliers and extreme values in individual scorer outputs. Fourth, it offers interpretational clarity, as the mean rank has a clear interpretation as the feature's averaged position in the significance-ordered list. Within the overall workflow shown in Fig. 7, the modified Borda stage is used to calculate the mean rank for consolidated feature ordering.

The execution of the workflow shown in Fig. 7 is parameterized as follows.

Stage I (Data preparation for analysis). The analytical feature matrix produced by the preprocessing pipeline of Fig. 6 is supplied as the common input to all five feature significance scorers, ensuring that ranking differences across scorers reflect the mathematical properties of the scorers rather than differences in feature representation.

Stage II (Feature significance assessment). Each of the five scorers (AUC, MI, dCor, LogReg, DecTree) produces a per-feature significance score on this common input, using the specific implementations and hyperparameters detailed in the per-scorer descriptions above.

Stage III (Modified Borda rank aggregation). Per-scorer scores are independently transformed into ranks using Eq. (1); these ranks are aggregated into the consolidated ordering using Eq. (2), in contrast to the classical sum-of-positions Borda score. The Python implementation of this aggregation is provided in Appendix B. Output. The output of the workflow is the consolidated ranking of features, which is examined empirically in Sections 4 and 5. By construction, this multi-stage procedure compensates for the methodological limitations of any individual scorer and provides a more reliable and balanced assessment of feature significance for subsequent use in modeling processes and decision-making.

4. Results

Upon applying the multi-algorithmic method described in Section 3 to the analyzed dataset, we derived feature importance scores for each of the five feature significance scorers. These raw scores, shown in Table 1, are subsequently transformed into per-scorer ranks via Eq. (1) and consolidated through the modified Borda mean rank of Eq. (2) into the ordering visualized in Fig. 8.

Subsequently, we constructed a heatmap depicting the relative significance of features across these scorers (see Fig. 8), where the numbers in the cells correspond to the per-scorer ranks computed using Eq. (1), "Average Rank" denotes the mean rank calculated using Eq. (2), and "Overall Rank" represents the final aggregated ordering (ties in "Average Rank" share the same overall rank).

Table 1. Feature importance scores by different scorers

Technical Feature Name	AUC	MI	dCor	LogReg	DecTree
order_messages	0.7708	0.1323	0.4512	2.7226	0.41
order_amount	0.5537	0.1077	0.2287	2.8973	0.1506
partner_success_rate	0.6952	0.0604	0.3834	0.906	0.1474
order_changes	0.6418	0.0432	0.2873	0.8465	0.0363
partner_success_avg_messages	0.5285	0.0531	0.1873	0.378	0.0026
partner_total_orders	0.5859	0.0174	0.1128	0.364	0
partner_total_messages	0.5896	0.0171	0.116	0.3362	0
partner_fail_avg_changes	0.5386	0.0191	0.0815	0.3101	0
create_date_months	0.5252	0.0166	0.1157	0.0547	0.2304
partner_success_avg_amount	0.5606	0.0719	0.1067	0.1775	0.0166
partner_avg_changes	0.5698	0.0195	0.1528	0.1591	0
partner_success_avg_changes	0.5393	0.0504	0.1786	0.1226	0
order_lines_count	0.5826	0.0377	0.1672	0.0739	0.0058
partner_fail_avg_messages	0.5425	0.0202	0.0804	0.1589	0.0004
partner_order_age_days	0.5751	0.0218	0.1337	0.0062	0
partner_avg_amount	0.5146	0.0212	0.0939	0.074	0
partner_fail_avg_amount	0.5033	0.0637	0.051	0.0134	0
source	0.5009	0.0214	0	0.0857	0
salesperson	0.5201	0.0155	0	0.0314	0
hour_of_day	0.5094	0.0098	0	0	0
month	0.5059	0.0122	0	0	0
discount_total	0.5002	0.0003	0.0105	0.0071	0
day_of_week	0.5003	0.0129	0	0	0
quarter	0.5	0.0101	0	0	0

Among the values reported in Table 1, ‘order_messages’ shows the highest scores across all five scorers (AUC = 0.7708, MI = 0.1323, dCor = 0.4512, LogReg = 2.7226, DecTree = 0.41). By contrast, ‘order_amount’ displays a less uniform pattern, with comparatively high values for MI = 0.1077 and LogReg = 2.8973, but a lower AUC = 0.5537. A similar cross-method difference is observed for ‘partner_success_rate’, which attains relatively high AUC = 0.6952 and dCor = 0.3834 values, while its MI score remains lower (0.0604). At the lower end of the table, ‘discount_total’ and the fine-grained temporal features (‘hour_of_day’, ‘month’, ‘day_of_week’, ‘quarter’) show near-baseline or zero values across most scorers.

Specifically, AUC gives the highest evaluation to features related to communication and customer success history. We observe a clear hierarchy in which current order characteristics and key historical metrics, such as ‘partner_success_rate’, are most significant, while categorical and temporal features are least important. MI gives greater weight to financial indicators compared to other scorers, with three of the top 5 features relating to financial indicators, particularly order amount (‘order_amount’), average amount of successful customer orders (‘partner_success_avg_amount’), and average amount of failed customer orders (‘partner_fail_avg_amount’). Additionally, MI assigns a non-trivial importance to the order source ('source'), a feature largely ignored by other scorers like dCor and Decision Tree.

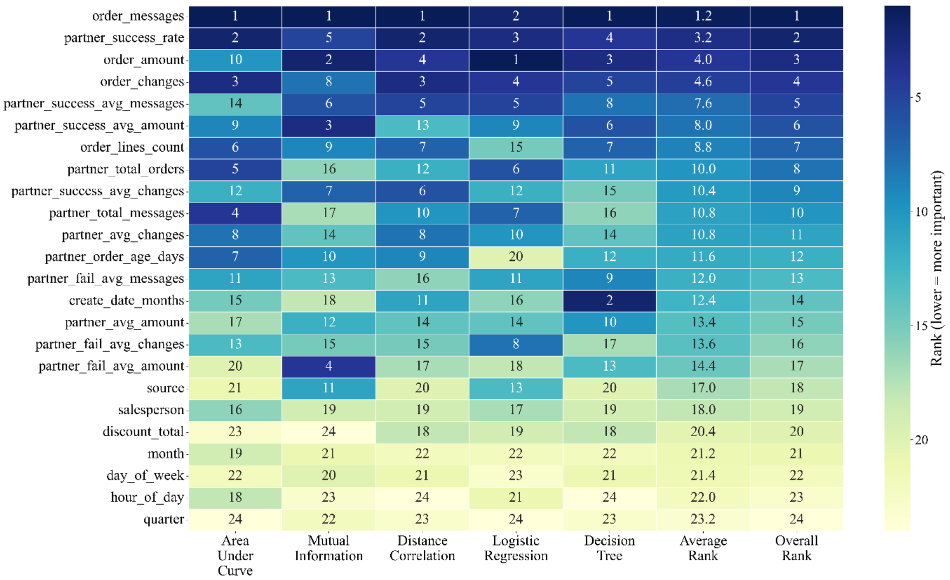

Figure 8. Feature importance rank heatmap by different scorers

dCor results are similar to AUC but with less distinction between values. However, for the most granular temporal features (hour, day, month, quarter), their unimportance is clearly demonstrated by zero correlation, suggesting the absence of significant nonlinear dependence between them and order success. LogReg clearly identifies ‘order_amount’ and ‘order_messages’ as the most important features, while rating the average number of changes in failed customer orders (‘partner_fail_avg_changes’) relatively high compared to other scorers. DecTree demonstrates the greatest selectivity in feature importance, identifying ‘order_messages’, ‘create_date_months’, and ‘order_amount’ as the most important, and concentrating the importance of success information in 9 key features. Based on these results, we can conclude that different feature significance scorers complement each other, enabling a comprehensive understanding of the predictors of order success in the studied system. This aligns with the study's results (González-Flores et al., 2025), which analyzed 15 B2B lead classification algorithms and showed that algorithm effectiveness varies depending on context.

To provide empirical confirmation of the aggregated ranking results, we present a set of binned success-rate plots illustrating how selected predictors relate to order success. Each visualization combines binned or categorical success rates with compact statistical summaries, including sample-size information, relevant association metrics, fitted trends where applicable, and Wilson-based uncertainty summaries for success rates.

The success rate demonstrates a pronounced positive correlation with the number of exchanged messages (`order_messages`). Across 20 equal-frequency bins (N = 86,794), the success rate increases from 7.7% for 1–3 messages to 90.2% for 23–282 messages. The association is statistically pronounced (Spearman rho = 0.454, $p < 0.001$; point-biserial r = 0.282, $p < 0.001$), and the weighted linear trend is 3.75 percentage points per bin ($R^2 = 0.806$; see Fig. 9).

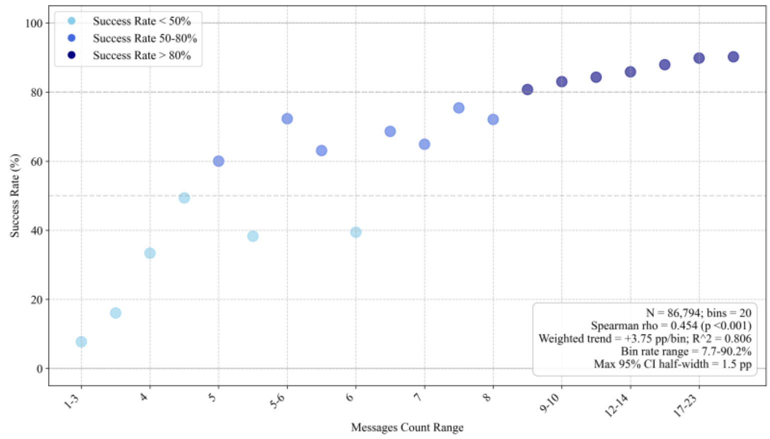

Figure 9. Success rate by message count

An overall positive trend is observed between the number of order modifications (`order_changes`) and the success rate. Orders with minimal changes (0–2) exhibit the lowest success rate (45.9%), while orders with 6 or more changes achieve 86.3%. The positive association is confirmed by Spearman rho = 0.241 ($p < 0.001$) and point-biserial r = 0.194 ($p < 0.001$), with a weighted trend of 6.45 percentage points per bin ($R^2 = 0.640$; see Fig. 10). This indicates that iterative alignment with customer requirements is associated with higher completion probability.

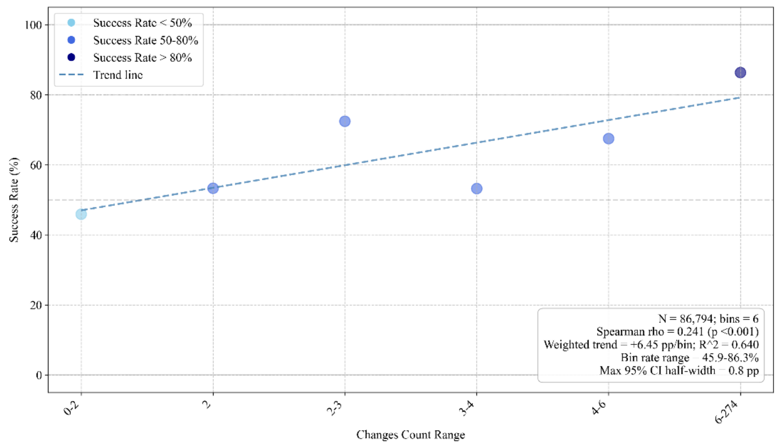

Figure 10. Success rate by changes count

The relationship between success rate and order amount (`order_amount`) exhibits a nonlinear, inverted U-shaped pattern. Among orders with a positive amount (N = 67,242), maximum success is observed in the mid-range price segment, peaking at 84.2% in the 710–789 USD bin. Both near-zero orders (5.3%) and high-value orders above approximately 6,000 USD (<50%) demonstrate substantially lower success rates. The monotonic association is negative but modest (Spearman rho = -0.150, $p < 0.001$; point-biserial r = -0.117, $p < 0.001$), whereas the quadratic fit explains the binned pattern much better ($R^2 = 0.736$; see Fig. 11). This nonlinearity is one of the reasons for the discrepancy in the assessments of the importance of this feature across different scorers.

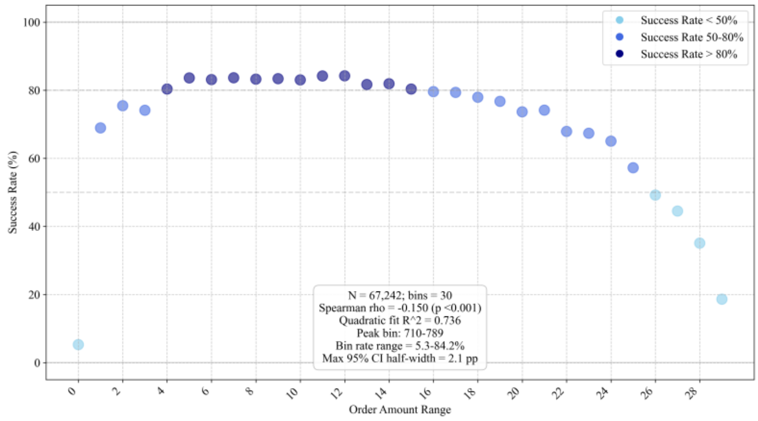

Figure 11. Success rate by order amount

Discount-related variables demonstrate weak marginal effects. Orders without discounts have a 63.1% success rate (n = 86,705), whereas orders with discounts have a 73.0% success rate (n = 89). This difference is borderline in a two-proportion test (p = 0.052) and has a negligible effect size (Cramer's V = 0.007). Within the positive-discount subset, success rates range from 55.6% to 83.3% across five bins, but the very small sample and wide confidence intervals (maximum Wilson 95% CI half-width = 20.9 percentage points) make this pattern exploratory rather than confirmatory (see Fig. 12).

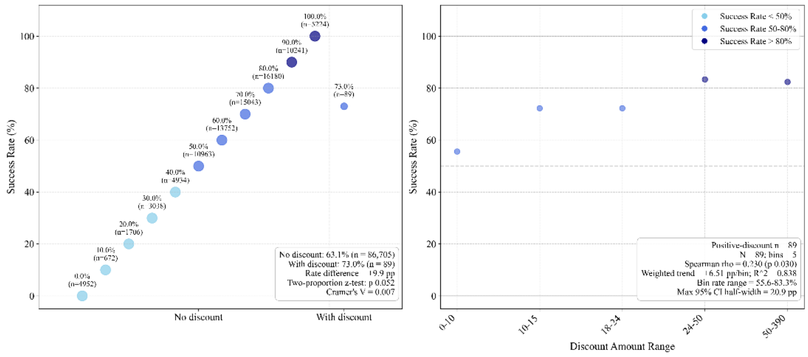

Figure 12. Success rate by discount

Success rate variation across weekdays is minimal: values range from 61% to 72%, with no pronounced pattern. Friday exhibits the lowest rate (61.3%), while Saturday and Sunday show slightly higher values (70.5% and 72.1%, respectively), although weekend order counts are small (139 and 122). The chi-square test is statistically significant due to the large total sample ($\chi^2(6) = 51.23$, $p < 0.001$), but the effect size is negligible (Cramer's V = 0.024), confirming the consolidated low importance of temporal factors in the ranking (see Fig. 13). Point size is proportional to the number of orders on each day.

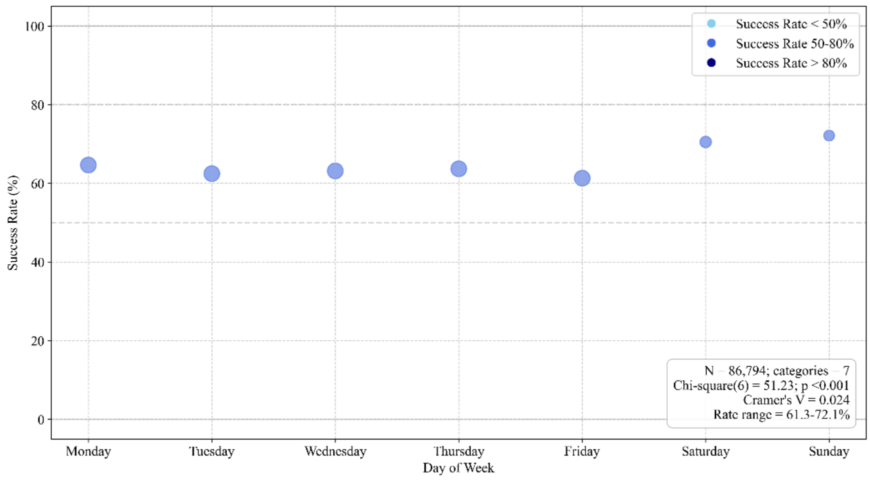

Figure 13. Success rate by day of week

The presented visualizations serve as marginal (single-feature) illustrations that complement the multi-scorer feature ranking by making the functional form of each relationship explicit. Communication intensity (`order_messages`) and order flexibility (`order_changes`) exhibit positive associations with success, corroborating their leading positions in the aggregated ranking. The nonlinear, inverted U-shaped dependence of `order_amount` explains the divergent importance scores across scorers. Discount and temporal variables show negligible or sample-limited effects, consistent with their low consolidated ranks. These empirical patterns reinforce the quantitative findings and highlight the primacy of interaction quality over monetary and temporal factors in B2B order outcomes.

Overall, the aggregated ranking indicates that the analyzed predictors form several empirical groups of B2B order success determinants, including communication-related, customer-history, order-flexibility, financial, and temporal factors. Communication-related and customer-history variables occupy the highest positions in the consolidated ranking, order-flexibility factors show intermediate importance, whereas financial indicators remain heterogeneous and temporal factors consistently rank among the weakest predictors in the analyzed dataset.

5. Discussion

Ranking results confirm the key role of communication in determining order success, as most scorers identified message count as the most important factor. This result aligns with the study's conclusions (Fraccastoro et al., 2020), which emphasize that communication tools are fundamental for establishing and maintaining relationships across various B2B process stages. Research on digital communication in business networks (Sashi, 2021) also confirms the role of technological innovations in value co-creation. Empirical studies of communication's influence on purchase decisions (Popescu et al., 2017) demonstrate that communication aspects can determine choice regardless of direct product utility. Research on the influence of the communication process on construction enterprise sales (Akintelu et al., 2023) emphasizes the importance of communication within ongoing business relationships.

The substantial influence of historical interaction experience, expressed through the average percentage of successful customer orders (‘partner_success_rate’), is confirmed by the second position, correlating with the RFID model for the B2B environment (Marín Díaz et al., 2022) and studies of customer loyalty to companies and loyalty programs (Evanschitzky et al., 2011). Similar dependence is confirmed by observations (Ferro-Soto et al., 2025) and research on customer loyalty factors for client retention in a digital environment (Pereira et al., 2025).

The order amount, identified by LogReg and MI scorers as most important, ranks only tenth by AUC, suggesting its influence depends on the chosen evaluation method. The study (Sadaram et al., 2023) explains this through volatility and the presence of noisy signals in financial metrics. The low significance of the total discount amount (20th place) contradicts common perceptions. Research on discount perception (Jee, 2021) shows a positive influence of price incentives, but, according to the results of this study, relationship quality parameters proved more important in the B2B context.

The importance of flexibility and adaptability to customer requirements during order processing is confirmed by order_changes' fourth position in the ranking. Recent research (Guesalaga et al., 2023) confirms flexibility as a critical success factor for B2B interactions.

The particularly low importance of temporal indicators suggests relative independence of order success from temporal patterns, contradicting research on demand seasonality (Guo et al., 2021) and industry research on seasonal conditions' influence (Smith, 2025). Such results can be attributed to the greater levels of organization and standardization characteristic of well-established B2B environments, which enhance business process predictability, as demonstrated in the study (Rezazadeh, 2020).

These findings demonstrate remarkable consistency with our previous research on the same dataset using different methods. Four features exhibited the highest predictive importance across all three studies: (1) ‘order_messages’ emerged as the dominant factor: rank 1 in the current multi-algorithmic analysis, highest weight (0.5421) in our statistical study (Miroshnychenko and Vovna, 2025), and among nine stable features in the XGBoost selection study (Miroshnychenko et al., 2025); (2) ‘order_changes’ showed consistent importance: rank 4 (current), rank 3 with weight 0.2828 (Miroshnychenko and Vovna, 2025), and top-9 stable (Miroshnychenko et al., 2025); (3) ‘order_lines_count’ reflecting order complexity: rank 7 (current), rank 6 with weight 0.1666 (Miroshnychenko and Vovna, 2025), and top-9 stable (Miroshnychenko et al., 2025); (4) ‘partner_success_avg_amount’ capturing historical financial performance: rank 6 (current), rank 9 with weight 0.1307 (Miroshnychenko and Vovna, 2025), and top-9 stable (Miroshnychenko et al., 2025).

Notably, ‘partner_success_rate’ ranked second in both the current analysis and statistical study (Miroshnychenko and Vovna, 2025) (weight 0.3956), but was excluded from the top-9 universally selected features in (Miroshnychenko et al., 2025), suggesting partial redundancy with related partner metrics.

This cross-methodological triangulation strengthens confidence in these factors as fundamental determinants of B2B order success rather than scorer-specific artifacts.

Distinguishing confirmatory from novel contributions. The factor-by-factor agreement reported above with prior single-method or single-discipline studies represents the confirmatory component of the present work. The novel component, in contrast, lies in three elements that have not been systematically combined in the existing B2B order-success literature: (i) the selection and methodological justification of five heterogeneous feature significance scorers that capture complementary forms of dependence between predictors and a binary outcome; (ii) a scorer-neutral, scale-independent aggregation method – the modified Borda mean rank – whose properties (methodological neutrality, scale invariance, robustness to outliers in individual scorer outputs, interpretational clarity) are explicitly argued for, rather than implicitly assumed; and (iii) a reproducible end-to-end pipeline that connects raw structured transactional data, type-specific preprocessing, scorer-specific feature ranking, and rank aggregation, with ERP-based B2B order data used here as an empirical demonstration rather than as the boundary of applicability.

Theoretical implications. The results are consistent with a relational view of B2B transactions, in which the probability of order completion is strongly associated with the quality and intensity of dyadic interaction rather than with transactional or temporal context alone. From a methodological standpoint, the modified Borda mean rank enables a stability-oriented interpretation of feature importance by comparing scorer-specific ranks: features whose ranks vary substantially across scorers (e.g., ‘order_amount’) are not necessarily uninformative, but their predictive contribution is non-monotonic and scorer-sensitive, and should therefore be treated with scorer-aware care. This complements the predictive-accuracy criterion that dominates ML-driven sales forecasting (Rohaan et al., 2022; Bauskar, 2024) with an assessment of how robust feature-importance conclusions are across heterogeneous scorers, thereby addressing the divided-opinions issue identified in Section 2.

Practical implications. Operationally, the proposed method provides a generic integration pattern for decision-support workflows based on structured transactional data: (i) the five feature significance scorers are run on the pre-processed feature matrix; (ii) the resulting ranks are consolidated using the modified Borda mean rank rule; and (iii) the consolidated ranking, together with the spread of scorer-specific ranks visible in the ranking heatmap, can be used as a feature-importance layer in the analyzed decision-support process (in Odoo, for instance, on top of ‘sale.order’ records). When instantiated on the analyzed dataset, this pattern produces the dataset-specific ranking reported in Table 1 and discussed above; when applied to another structured dataset, ERP deployment, or B2B segment, it is expected to yield a different factor ordering. The prescriptive content of this study is therefore the proposed method and its reproducible application procedure, rather than any universal list of B2B success factors.

Despite the validity of the obtained results, this study has certain methodological limitations. First, the analysis is based on data from a single Odoo system, which may limit the generalizability of the conclusions to other ERP systems or industries. Second, the study focuses on quantitative characteristics of orders and communication but does not account for qualitative aspects and communication topics.

6. Conclusions

This study identified key factors influencing B2B order success in the Odoo ERP system using a multi-algorithmic ranking method that combines five feature significance scorers (AUC, MI, dCor, LogReg, DecTree) and aggregates results through a modified Borda rank-aggregation rule based on the arithmetic mean of scorer-specific ranks, thereby increasing the reliability of the conclusions. The proposed method is intended as a generalizable framework for structured transactional data, whereas the specific ordering and grouping of factors reported here reflect the empirical structure of the analyzed ERP-based dataset. The most stable and influential determinants of order success are communication intensity and customer-history characteristics, with the number of exchanged messages emerging as the strongest overall predictor and historical partner success also occupying the highest positions in the consolidated ranking. Order-flexibility factors retain secondary importance, indicating that iterative adjustment of order parameters is positively associated with successful completion. Financial indicators, particularly order amount, remain scorer-dependent, suggesting that their role is more complex and less consistent across scorers, whereas discount-related and fine-grained temporal variables contribute comparatively little to the consolidated ranking. Beyond these factor-level findings, the principal scientific contributions of the work are threefold: (i) the selection and methodological justification of five mathematically heterogeneous feature significance scorers that capture complementary forms of dependence between predictors and a binary outcome; (ii) a scorer-neutral aggregation method – the modified Borda mean rank – that transforms heterogeneous scorer-specific outputs into a consolidated, scale-independent ranking whose methodological neutrality, scale invariance, robustness to outliers, and interpretational clarity are explicitly argued for; and (iii) a reproducible end-to-end pipeline that operationalizes this method on structured transactional data and can be applied to other datasets and decision-support contexts, including but not limited to ERP systems. The proposed method can be implemented for automated order success forecasting and tested in other structured transactional domains. Future research should focus on analyzing factor interactions, testing the method on additional datasets, and developing a predictive system for order success based on the key factors identified in this empirical application.

List of abbreviations

ML	Machine Learning
AUC	Area Under the Curve
B2B	Business-to-Business
dCor	Distance Correlation
DecTree	Decision Trees
ERP	Enterprise Resource Planning
LogReg	Logistic Regression
MI	Mutual Information
OHE	One-Hot Encoding
ROC	Receiver Operating Characteristic

References

Akintelu, S. O., Oyebola, A. I., Tiamiyu, S., Olateju, O. (2023). The impact of project communication management on successful project delivery in the construction industry: A case study, *Int. J. Dev. Sustain*., 12, 376–386.

Bauskar, S. (2024). Predictive Analytics For Sales Forecasting In Enterprise Resource Planning (Erp) Systems Using Machine Learning Technique, *SSRN Electron. J.* DOI: 10.2139/ssrn.4988774.

Breiman, L., Friedman, J. H., Olshen, R. A., Stone, C. J. (2017). *Classification and Regression Trees*, Routledge: New York, NY, USA. DOI: 10.1201/9781315139470.

Calders, T., Jaroszewicz, S. (2007). Efficient AUC Optimization for Classification. In: Knowledge Discovery in Databases: PKDD 2007. *Lecture Notes in Computer Science*; Kok, J. N., Ed.; Springer: Berlin/Heidelberg, Germany, 4702, 42–53. DOI: 10.1007/978-3-540-74976-9_8.

Chakraborty, D., Elzarka, H. (2018). Advanced machine learning techniques for building performance simulation: a comparative analysis, *J. Build. Perform. Simul*., 12, 193–207. DOI: 10.1080/19401493.2018.1498538.

Dekking, F. M., Kraaikamp, C., Lopuhaä, H. P., Meester, L. E. (2005). *A Modern Introduction to Probability and Statistics*, Springer: London, UK. DOI: 10.1007/1-84628-168-7.

Dwork, C., Kumar, R., Naor, M., Sivakumar, D. (2001). Rank aggregation methods for the Web. In: *Proceedings of the 10th International Conference;* ACM Press: New York, NY, USA. DOI: 10.1145/371920.372165.

Eid, R., Trueman, M., Ahmed, A. M. (2002). A cross-industry review of B2B critical success factors, *Internet Res*., 12, 110–123. DOI: 10.1108/10662240210422495.

Evanschitzky, H., Ramaseshan, B., Woisetschläger, D. M., Richelsen, V., Blut, M., Backhaus, C. (2011). Consequences of customer loyalty to the loyalty program and to the company, *J. Acad. Mark. Sci*., 40, 625–638. DOI: 10.1007/s11747-011-0272-3.

Fawcett, T. (2006). An introduction to ROC analysis, *Pattern Recognit. Lett*., 27, 861–874. DOI: 10.1016/j.patrec.2005.10.010.

Ferro-Soto, C., Padin, C., Lubbe, I., Svensson, G., Høgevold, N. (2025). Determinants and outcomes of satisfaction in B2B sales relationships, *J. Bus. Ind. Mark*., 40, 61–76. DOI: 10.1108/jbim-10-2022-0470.

Fraccastoro, S., Gabrielsson, M., Pullins, E. B. (2020). The integrated use of social media, digital, and traditional communication tools in the B2B sales process of international SMEs, *Int. Bus. Rev*., 29, 101776. DOI: 10.1016/j.ibusrev.2020.101776.

González-Flores, L., Rubiano-Moreno, J., Sosa-Gómez, G. (2025). The relevance of lead prioritization: a B2B lead scoring model based on machine learning, *Front. Artif. Intell*., 8, 1554325. DOI: 10.3389/frai.2025.1554325.

Guesalaga, R., Ruiz-Alba, J. L., López-Tenorio, P. J. (2023). Drivers of business-to-business sales success and the role of digitalization after COVID-19 disruptions, *J. Bus. Ind. Mark.*, 39, 708–720. DOI: 10.1108/jbim-12-2022-0576.

Günther, M. (2021). Performance in B2B Sales: An Explanation of How Channel Management and Communication Influence a Firm's Performance, *Naše Gospod. Our Econ.*, 67, 38–48. DOI: 10.2478/ngoe-2021-0016.

Guo, L., Fang, W., Zhao, Q., Wang, X. (2021). The hybrid PROPHET-SVR approach for forecasting product time series demand with seasonality, *Comput. Ind. Eng.*, 161, 107598. DOI: 10.1016/j.cie.2021.107598.

Høgevold, N. M., Rodriguez, R., Svensson, G., Roberts-Lombard, M. (2022). Organisational and environmental indicators of B2B sales performance, *Mark. Intell. Plan*., 40, 33–56. DOI: 10.1108/MIP-03-2021-0100.

Hrischev, R., Shakev, N. (2023). Artificial Intelligence in Enterprise Resource Planning Systems, *Eng. Sci.*, LX, 1–13. DOI: 10.7546/engsci.lx.23.01.01.

Jee, T. W. (2021). The perception of discount sales promotions – A utilitarian and hedonic perspective, *J. Retail. Consum. Serv*., 63, 102745. DOI: 10.1016/j.jretconser.2021.102745.

Kleinbaum, D. G., Klein, M. (2010). *Logistic Regression*, Springer: New York, NY, USA. DOI: 10.1007/978-1-4419-1742-3.

Kraskov, A., Stögbauer, H., Grassberger, P. (2004). Estimating mutual information, *Phys. Rev. E*, 69, 066138. DOI: 10.1103/physreve.69.066138.

Lee, F. (2025). What Is Logistic Regression? IBM – United States. Available online: https://www.ibm.com/think/topics/logistic-regression.

Lin, S.-W., Fu, H.-P., Lin, A. J. (2023). Critical success factors and implementation strategies for B2B electronic procurement systems in the travel industry, *J. Hosp. Tour. Technol.*, 14, 505–522. DOI: 10.1108/JHTT-08-2021-0230.

Marín Díaz, G., Galán, J. J., Carrasco, R. A. (2022). XAI for Churn Prediction in B2B Models: A Use Case in an Enterprise Software Company, *Mathematics*, 10, 3896. DOI: 10.3390/math10203896.

Miroshnychenko, S. O. (2024). Improvement of the existing functionality for forecasting finished goods inventory at the enterprise warehouses based on the stock forecasted report ERP ODOO. In: *Miningmetalteh 2024 – The Mining and Metals Sector: Integration of Business, Technology and Education*; Baltija Publishing: Riga, Latvia, 2, 48–51. DOI: 10.30525/978-9934-26-506-8-133.

Miroshnychenko, S. O., Koyfman, O. O., Miroshnychenko, V. I. (2024). The relevance of implementing an intelligent decision support system for enterprise resource optimization. In: *Miningmetalteh 2024 – The Mining and Metals Sector: Integration of Business, Technology and Education*; Baltija Publishing: Riga, Latvia, 2, 45–47. DOI: 10.30525/978-9934-26-506-8-132.

Miroshnychenko, S. O., Miroshnychenko, V. I., Koyfman, O. O., Vovna, O. V. (2025). Automated feature selection system for computer-integrated forecasting of B2B order success using XGBOOST, *Sci. J. Metinvest Polytech*. Ser. Tech. Sci., 5, 58–75. DOI: 10.32782/3041-2080/2025-5-7.

Miroshnychenko, S. O., Vovna, O. V. (2025). Multifactor statistical analysis of order success as a tool for optimizing automated resource management systems, *Bull. Priazovskyi State Tech. Univ*. Ser. Tech. Sci., 50, 182–190. DOI: 10.31498/2225-6733.50.2025.336372.

Pereira, M. d. S., Schmitt de Castro, B., Alves Cordeiro, B., Mendonça Peixoto, M. G., Cornils Monteiro da Silva, E., Carneiro Gonçalves, M. (2025). Factors of Customer Loyalty and Retention in the Digital Environment, *J. Theor. Appl. Electron. Commer. Res*., 20, 71. DOI: 10.3390/jtaer20020071.

Popescu, D., Dinu, A., State, C., Picu, C. (2017). Empirical Study Regarding the Influence of Communication Upon the Purchasing Decision, *Int. Conf. Knowl. Based Organ*., 23, 430–437. DOI: 10.1515/kbo-2017-0071.

Rezazadeh, A. (2020). A Generalized Flow for B2B Sales Predictive Modeling: An Azure Machine-Learning Approach, *Forecasting*, 2, 267–283. DOI: 10.3390/forecast2030015.

Rohaan, D., Topan, E., Groothuis-Oudshoorn, C. G. M. (2022). Using supervised machine learning for B2B sales forecasting: A case study of spare parts sales forecasting at an after-sales service provider, *Expert Syst. Appl*., 188, 115925. DOI: 10.1016/j.eswa.2021.115925.

Rodriguez, R., Roberts-Lombard, M., Høgevold, N. M., Svensson, G. (2022). Organisational and environmental indicators of B2B sellers' sales performance in services firms, *Eur. Business Rev*., 34, 578–602. DOI: 10.1108/EBR-05-2021-0123.

Ross, B. C. (2014). Mutual Information between Discrete and Continuous Data Sets, *PLoS ONE*, 9, e87357. DOI: 10.1371/journal.pone.0087357.

Sadaram, G., Jha, K. M., Katnapally, N. (2023). Optimising Sales Forecasts in ERP Systems Using Machine Learning and Predictive Analytics, *SSRN Electron. J.* DOI: 10.2139/ssrn.5114001.

Sarkar, C., Cooley, S., Srivastava, J. (2014). Robust Feature Selection Technique Using Rank Aggregation, *Appl. Artif. Intell*., 28, 243–257. DOI: 10.1080/08839514.2014.883903.

Sashi, C. M. (2021). Digital communication, value co-creation and customer engagement in business networks: a conceptual matrix and propositions, *Eur. J. Mark.*, 55, 1643–1663. DOI: 10.1108/ejm-01-2020-0023.

Smith, J. D. (2025). The Influence of Weather on Closing B2B Sales: Is it More Likely to Close a Sale on Sunny Days Versus Cloudy or Rainy Days? *Int. J. Res. Publ. Rev*., 6, 971–974. DOI: 10.55248/gengpi.6.0325.1127.

Székely, G. J., Rizzo, M. L., Bakirov, N. K. (2007). Measuring and testing dependence by correlation of distances, *Ann. Stat*., 35, 2769–2794. DOI: 10.1214/009053607000000505.

Ul Haq, I., Gondal, I., Vamplew, P., Brown, S. (2019). Categorical Features Transformation with Compact One-Hot Encoder for Fraud Detection in Distributed Environment. In: *Data Mining. AusDM 2018. Communications in Computer and Information Science*; Islam, R., Ed.; Springer: Singapore, 996, 53–65. DOI: 10.1007/978-981-13-6661-1_6.

Vambol, V., Kowalczyk-Juśko, A., Vambol, S., Khan, N., Mazur, A., Goroneskul, M., Kruzhilko, O. (2023). Multi criteria analysis of municipal solid waste management and resource recovery in Poland compared to other EU countries, *Sci. Rep*., 13, 21233. DOI: 10.1038/s41598-023-48026-3.

Wald, R., Khoshgoftaar, T. M., Dittman, D., Awada, W., Napolitano, A. (2012). An extensive comparison of feature ranking aggregation techniques in bioinformatics. In: *Proceedings of the 2012 IEEE 13th International Conference on Information Reuse & Integration (IRI),* Las Vegas, NV, USA, 8–10 August 2012; 377–384. DOI: 10.1109/IRI.2012.6303034.

Wilson, R. D., Stephens, A. M. (2023). The challenges of B2B innovation: using marketing analytics to plan and implement a successful digital catalog adoption, *J. Bus. Ind. Mark*., 38, 290–302. DOI: 10.1108/JBIM-12-2021-0598.

Zoltners, A. A., Sinha, P., Sahay, D., Shastri, A., Lorimer, S. E. (2021). Practical insights for sales force digitalization success, *J. Pers. Sell. Sales Manag*., 41, 87–102. DOI: 10.1080/08853134.2021.1908144.

Appendix A
Feature Name Mapping

Table 2. Feature Name Mapping

Technical Feature Name	Descriptive Name	Category	Data Type	Unit / Scale
order_messages	Number of messages exchanged per order	Communication	Integer	count
order_amount	Total monetary value of the order	Financial	Float	USD
partner_success_rate	Historical success rate of the partner	Partner History	Float	%
order_changes	Number of modifications made to the order	Order Flexibility	Integer	count
partner_success_avg_messages	Average number of messages in partner's successful orders	Communication / History	Float	count
partner_total_orders	Total number of historical orders by the partner	Partner History	Integer	count
partner_total_messages	Total messages across all partner orders	Communication / History	Integer	count
partner_fail_avg_changes	Average number of changes in partner's failed orders	Partner History	Float	count
create_date_months	Months elapsed since the first recorded order	Temporal	Integer	months since initial recorded order
partner_success_avg_amount	Average amount of partner's successful orders	Financial / History	Float	USD
partner_avg_changes	Average number of changes across all partner orders	Partner History	Float	count
partner_success_avg_changes	Average number of changes in partner's successful orders	Partner History	Float	count

Technical Feature Name	Descriptive Name	Category	Data Type	Unit / Scale
order_lines_count	Number of product lines in the order	Order Complexity	Integer	count
partner_fail_avg_messages	Average number of messages in partner's failed orders	Communication / History	Float	count
partner_order_age_days	Days since partner's first order in the system	Partner History	Integer	days
partner_avg_amount	Average amount across all partner orders	Financial / History	Float	USD
partner_fail_avg_amount	Average amount of partner's failed orders	Financial / History	Float	USD
source	Lead/order acquisition channel	Categorical	Object	category label
salesperson	Assigned sales representative identifier	Categorical	Object	category label
hour_of_day	Hour when the order was placed	Temporal	Integer	0–23
month	Month when the order was placed	Temporal	Object	month category
discount_total	Total discount applied to the order	Financial	Float	USD
day_of_week	Day of the week when the order was placed	Temporal	Object	weekday category
quarter	Quarter when the order was placed	Temporal	Integer	1–4

This appendix table reports the original substantive analytical features retained for interpretation prior to type-specific preprocessing. Their final machine-readable representation is generated subsequently through the transformations described in the Methods section, including cyclical sin/cos encoding for selected temporal variables, OHE Extended Compact encoding for categorical variables, and robust scaling for numerical variables.

Appendix B
Python Code for the Modified Borda Rank Aggregation

```
import pandas as pd
def modified_borda_mean_rank(method_scores: dict[str,
pd.Series])
-> pd.DataFrame:
    df = pd.DataFrame(method_scores)
    ranks = df.rank(ascending=False, method="max")
    ranks["mean_rank"] = ranks.mean(axis=1)
    ranks.insert(0, "feature", ranks.index)
    return
ranks.sort_values("mean_rank").reset_index(drop=True)
```

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