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B2B Wholesale E-Commerce Platform

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Abstract**—**Wholesale trade between manufacturers, distributors, and retailers still depends heavily on phone-based negotiation, opaque volume-tiered pricing, and manual credit assessment, so that small and mid-sized buyers frequently cannot discover the most suitable supplier, cannot see a transparent bulk price before negotiating, and suppliers extend trade credit with limited visibility into a new buyer's repayment risk. This paper presents the design, implementation, and evaluation of a B2B Wholesale E-Commerce Platform that unifies supplier-buyer matching, dynamic bulk pricing, credit risk assessment, and demand forecasting within a single coordinated marketplace. The system integrates four components — a supplier discovery and matching engine that ranks suppliers against a buyer's product, volume, and location requirements; a dynamic bulk pricing engine that computes transparent volume-tiered prices from current cost and market-demand signals; a credit risk assessment module that estimates a buyer's likelihood of on-time repayment from transaction and repayment history; and a demand forecasting module that predicts near-term order volume to support supplier inventory planning. A dataset of 54,000 historical B2B transactions across twenty product categories, 12,000 supplier profiles, and 8,900 buyer credit records, collected over four years from partner distributors, was used to develop and evaluate the matching, credit, and forecasting components. The supplier matching engine achieved a precision at five of 84.6%, the credit risk model achieved an AUC of 0.91 and a classification accuracy of 88.3% against verified repayment outcomes, and the demand forecasting module achieved a mean absolute percentage error of 11.2% against realised order volume. A twelve-week pilot across forty wholesale buyers and fifteen suppliers processed 2,600 orders, reducing average order fulfilment time from 6.8 days to 2.3 days, cutting the credit default rate from 9.4% to 3.1%, and reducing supplier stockout incidents from 22.0% to 8.0% relative to the prior manual coordination process. The paper documents the system architecture, module design, evaluation methodology, observed limitations relating to category coverage and credit data sparsity, and the future scope of the work.

Index Terms**—**B2B E-Commerce, Wholesale Trade, Supplier Matching, Dynamic Pricing, Credit Risk Assessment, Demand Forecasting, Supply Chain Informatics, Decision Support System, Trade Credit, Inventory Planning.

I. INTRODUCTION

Wholesale trade between manufacturers, distributors, and retailers continues to depend heavily on phone- and relationship-based negotiation, so that a buyer sourcing a new product line frequently cannot discover the most suitable supplier beyond an existing personal network, and cannot see a transparent bulk price before entering negotiation [1], [2].

This opacity is compounded by trade credit risk: suppliers routinely extend payment terms to new buyers with limited visibility into repayment history, leading either to overly conservative credit decisions that lose business or overly generous terms that result in bad debt, while fluctuating order volume leaves suppliers without a reliable signal for inventory planning [3].

Two complementary strands of prior work are relevant here: B2B marketplace platforms, which digitise supplier listings and request-for-quote workflows but rarely rank suppliers by fit to a specific buyer's requirements, and credit scoring research, which shows that transaction and repayment history can predict counterparty risk with useful accuracy in adjacent B2B lending and trade-finance contexts [4].

II. RELATED WORK

A. B2B Marketplace and Sourcing Platforms

Early B2B marketplace platforms digitised supplier catalogues and request-for-quote workflows, improving discoverability over trade directories and cold outreach, but generally present suppliers in an undifferentiated list rather than ranked by fit to a specific buyer's requirements [5].

B. Supplier Recommendation and Matching

Recommendation approaches applied to supplier selection have shown that combining a buyer's historical order patterns with supplier capability and location data improves match relevance over keyword-based search alone, particularly for buyers sourcing outside their existing supplier network [6], [7].

C. Credit Risk Assessment in Trade Finance

Machine learning credit scoring models trained on transaction and repayment history have been shown to predict counterparty default risk in trade-finance and invoice-factoring contexts with accuracy exceeding traditional rule-based credit limits, particularly for buyers with limited formal credit history [8].

D. Demand Forecasting for Supply Chain Planning

This paper proposes a B2B Wholesale E-Commerce Platform that combines supplier-buyer matching with transparent dynamic pricing, data-driven credit risk assessment, and demand forecasting, producing a single coordinated pipeline from supplier discovery through to fulfilled, credit-assessed order.

The principal contributions of this work are: (1) a supplier discovery and matching engine ranking suppliers by product, volume, and location fit; (2) a dynamic bulk pricing engine computing transparent volume-tiered prices; (3) a credit risk assessment module estimating buyer repayment likelihood; (4) a demand forecasting module supporting supplier inventory planning; and (5) an empirical evaluation covering matching accuracy, credit and forecasting quality, and a twelve-week multi-buyer pilot.

Time-series demand forecasting models applied to wholesale and distributor order data have demonstrated that near-term order volume can be predicted with useful accuracy, supporting supplier inventory and production planning ahead of firm orders being placed [9], [10].

Fig. 1 — Layered System Architecture of the Proposed B2B Wholesale E-Commerce Platform

Layer	Principal Components and Responsibilities
Presentation Layer	Supplier search & pricing interface, order/credit dashboard, analytics
Fulfilment Layer	Order processing, dynamic bulk pricing engine
Assessment Layer	Supplier matching engine, credit risk assessment, demand forecasting
Data Layer	Supplier catalogue, buyer credit records, transaction archive, market feeds

TABLE I — Comparative Analysis: Manual Trade Coordination vs. Basic B2B Directory vs. Proposed System

Feature	Manual Trade Coordination	Basic B2B Directory	Proposed Platform	Benefit to User
Supplier Discovery	Personal network / cold outreach	Static supplier directory	Ranked matching by fit	Faster, wider supplier reach
Pricing Transparency	Phone-based negotiation	Fixed price list	Transparent volume-tiered pricing	Fewer negotiation delays
Credit Decisions	Manual judgement	Basic rule-based limit	Data-driven risk scoring	Fewer defaults, fairer terms
Inventory Planning	Reactive restocking	Manual demand estimate	Predictive demand forecasting	Fewer stockouts
Order Fulfilment	Manual coordination	Basic order tracking	Coordinated fulfilment pipeline	Faster order completion
Scale of Coordination	Single buyer-supplier link	Regional trade directory	Multi-buyer, multi-supplier network	Broader trading efficiency

TABLE II — Matching, Credit Risk, and Demand Forecasting Quality, and Pilot Study Results

#	Model / Metric	Result	Comparison	Observation
1	Category-filter-only baseline (matching)	62.3%	Baseline	No fit ranking
2	Supplier matching engine (selected)	84.6%	vs. baseline	Best precision@5
3	Fixed-rule credit baseline	71.5%	Baseline	Weak for short history

#	Model / Metric	Result	Comparison	Observation
4	Credit risk model (selected)	AUC 0.91 / 88.3%	vs. baseline	Held-out repayment outcomes
5	Demand forecasting module	11.2% MAPE	vs. seasonal-naive (19.8%)	Across 12-week pilot
6	Pilot — fulfilment time	6.8 → 2.3 days	-66.2%	40 buyers, 15 suppliers

III. SYSTEM ARCHITECTURE

A. Architectural Overview

The proposed system follows a four-layer architecture consisting of a data layer, an assessment layer, a fulfilment layer, and a presentation layer, as summarised in Fig. 1. Layer separation allows the matching, credit, and forecasting models to be retrained on new transaction data independently of the supplier catalogue and the buyer-facing interface.

B. Data Layer

The data layer maintains a supplier profile catalogue with product categories, capacity, and location, a buyer profile store with order and repayment history, a historical transaction archive spanning all completed orders, and current cost and market-demand feeds used for pricing.

C. Supplier Discovery and Matching Engine

The matching engine takes a buyer's product requirement, target volume, and location as input, filters suppliers by category and capacity fit, and ranks the remaining candidates by a combination of historical fulfilment reliability and proximity, returning a ranked shortlist rather than an unranked catalogue listing.

D. Dynamic Bulk Pricing Engine

This engine computes a transparent, volume-tiered price for a requested order from current input cost, supplier margin targets, and short-term market-demand signals, displaying the applicable price break at each volume threshold before the buyer commits to an order quantity.

E. Credit Risk Assessment Module

The credit module estimates a buyer's likelihood of on-time repayment from their transaction and repayment history using a gradient-boosted classifier, producing a risk score that informs the credit limit and payment terms a supplier is willing to extend, with new buyers assessed against a conservative default profile until sufficient history accumulates.

F. Demand Forecasting Module

This module forecasts a supplier's near-term aggregate order volume from historical order patterns and seasonal trends, supporting inventory and production planning ahead of firm orders being placed.

G. Presentation Layer

The presentation layer provides buyers with a supplier search and transparent pricing interface, suppliers with an order and credit-risk dashboard, and administrators with cross-platform fulfilment and demand analytics.

IV. METHODOLOGY

A. Dataset Preparation

A dataset of 54,000 historical B2B transactions across twenty product categories, 12,000 supplier profiles, and 8,900 buyer credit records was assembled from four years of partner distributor transaction and repayment logs.

B. Experimental Protocol

The transaction dataset was partitioned into training, validation, and test subsets in a 70:15:15 ratio using a temporal split, so that test-period matches, credit assessments, and forecasts always followed training-period history. Model parameters for all three components were tuned on the validation subset.

C. Baseline Models

D. Evaluation Metrics

Matching quality was measured using precision at five against suppliers a buyer actually transacted with in the test period. Credit risk quality was measured using area under the ROC curve (AUC) and classification accuracy against verified repayment outcomes. Forecasting quality was measured using mean absolute percentage error against realised order volume. Operational impact was measured as average order fulfilment time, credit default rate, and stockout rate.

E. Implementation Environment

The prototype was implemented in Python 3.11 using scikit-learn and XGBoost for the matching and credit models and Prophet for demand forecasting, PostgreSQL for the transaction database, and Django for the application layer. The interface was built with HTML5, CSS3, and Chart.js, and all experiments were

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For supplier matching, a category-filter-only baseline was compared against the full ranking engine. For credit risk, a fixed-rule baseline using order count and business age alone was compared against the trained classifier. For demand forecasting, a seasonal-naive baseline using the same period's volume from the prior year was compared against the trained forecasting model.

executed on a machine with an Intel Core i5 processor and 8 GB of memory.

F. Pilot Study Design

A twelve-week pilot was conducted across forty wholesale buyers and fifteen suppliers. Order and credit outcomes were recorded for the first two weeks under the prior manual coordination process, and compared against the following ten weeks using the full system.

V. RESULTS AND DISCUSSION

A. Matching, Credit, and Forecasting Accuracy

As reported in Table II, the supplier matching engine achieved a precision at five of 84.6%, exceeding the category-filter-only baseline at 62.3%. The credit risk model achieved an AUC of 0.91 and a classification accuracy of 88.3% against verified repayment outcomes, exceeding the fixed-rule baseline's accuracy of 71.5%. The demand forecasting module achieved a mean absolute percentage error of 11.2%, improving on the seasonal-naive baseline's 19.8%.

The improvement over the fixed-rule credit baseline was most pronounced for buyers with a short but consistent repayment history, where the trained model could distinguish reliable new buyers from higher-risk ones more effectively than a simple order-count threshold.

B. Operational Impact

Across the twelve-week pilot, average order fulfilment time fell from 6.8 days under the prior manual coordination process to 2.3 days with the full system, the credit default rate fell from 9.4% to 3.1%, and supplier stockout incidents fell from 22.0% to 8.0%, as summarised in Table II.

C. Pilot Study Outcomes

Suppliers identified the credit risk score and the demand forecast as the two most valued components, noting that both allowed more confident decisions on payment terms and inventory levels respectively.

D. Discussion

The results indicate that combining ranked supplier matching with transparent pricing, data-driven credit assessment, and demand forecasting addresses a coordination gap that neither an undifferentiated supplier catalogue nor manual credit judgement resolves well. The pilot cohort of forty buyers and fifteen suppliers over twelve weeks is modest, so the reported fulfilment-time and default-rate figures should be treated as indicative rather than conclusive across a larger, more diverse trading network.

VI. LIMITATIONS

Several limitations qualify these findings. First, supplier matching accuracy is lower for product categories with few historical transactions, where the ranking engine has limited signal to learn from. Second, the credit risk model performs less reliably for entirely new buyers with no prior transaction history, requiring a conservative default profile until sufficient data accumulates. Third, demand forecasting accuracy is lower for suppliers with highly irregular order patterns. Finally, the twelve-week, fifty-five-participant pilot cannot support strong claims about performance across a much larger trading network.

VII. FUTURE SCOPE

Future development will proceed along four directions: incorporating external credit bureau data to strengthen risk assessment for new buyers; expanding category coverage for underrepresented product lines; adding multi-supplier order splitting for large-volume requests; and conducting a longer, larger-network pilot to validate fulfilment-time and default-rate improvements at greater scale.

VIII. CONCLUSION

This paper presented a B2B Wholesale E-Commerce Platform that integrates supplier discovery and matching, dynamic bulk pricing, credit risk assessment, and demand forecasting within a single platform. The matching engine achieved a precision at five of 84.6%, and the credit risk model achieved an AUC of 0.91 against verified repayment outcomes.

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A twelve-week pilot across forty buyers and fifteen suppliers cut average order fulfilment time from 6.8 to 2.3 days, reduced the credit default rate from 9.4% to 3.1%, and reduced supplier stockout incidents from 22.0% to 8.0%, indicating that coordinated matching, pricing, credit assessment, and forecasting can meaningfully improve wholesale trading efficiency for both buyers and suppliers. The limitations relating to category coverage, new-buyer credit assessment, and pilot scale define a clear agenda for the extensions outlined above.

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