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Article

# AI-Driven Intelligence Layer 4 SME-to-B2B Marketplace Optimization: The AISLE Framework

**Dr. R. Geetha[1], Dr. P. Selvi[2], Dr. R. Manju[3], Dr. K. Mahendran[4], Dr. K. Kannan[5]*, Dr. T. Mohan[6]**

[1] Associate Professor, Department of Commerce – Corporate Secretaryship with CA, Dr. N.G.P. Arts and Science College, Coimbatore, Tamil Nadu, India.
[2] Assistant Professor, Department of Commerce with Banking and Insurance, Sri Ramakrishna College of Arts & Science, Coimbatore, Tamil Nadu, India.
[3] Assistant Professor, Department of Commerce with Computer Applications, Sri Krishna Adithya College of Arts and Science, Kovaipudur, Coimbatore – 641042, Tamil Nadu, India. Email: manjugeethu19@gmail.com ORCID: 0009-0002-7389-7616
[4] Assistant Professor, Department of Corporate Secretaryship, Dr. N.G.P. Arts and Science College, Coimbatore – 641048, Tamil Nadu, India. Email: maheacs@gmail.com
[5] Assistant Professor in Economics, Department of Commerce with Computer Applications, Akshaya College of Arts and Science (Co-Education), Coimbatore – 642109, Tamil Nadu, India. ORCID: 0000-0001-7359-8160
[6] Assistant Professor, Department of Commerce CA, Swami Dayananda College of Arts & Science, Manjakkudi, Thiruvarur District, Tamil Nadu, India. Email: mohannet2012@gmail.com ORCID: 0000-0003-4827-2235 Vidwan ID: 288038
Corresponding Author: Dr. K. Kannan[5]

**Abstract:** Systemic inefficiencies in sourcing discovery, manual demand forecasting, and flawed pricing strategies are still an operational challenge for small and medium enterprises (SME) within the business-to-business (B2B) digital commerce. This paper presents the Adaptive Intelligence for SME-Led E-commerce (AISLE) framework, an adaptive intelligence layer for optimum operation of B2B marketplace for resource-limited organisations in emerging economies using artificial intelligence. AISLE combines three fundamental features – the machine learning-based supplier matching feature, the real-time demand prediction feature and the dynamic pricing optimization feature – all designed to run in the infrastructural and capital constraints typical of SMEs. The multi-phase empirical evaluation was performed over a six-month deployment period with 47 SMEs from retail, manufacturing and logistics from India and Southeast Asia. The quantitative results show that ML-driven supplier matching can cut the search time by as much as 68% and increase the accuracy of order forecasting by 28.7% while adding gross margin improvements of between 12% and 18%. Three approaches of scalable architectures are suggested: (1) lightweight recommendation engines capable of deployment on constrained infrastructure, (2) federated learning mechanisms that support organizational data privacy while also providing shared learning power across the organization, and (3) cost-effective API-first integration approaches that work with legacy ERP and in-store systems. The AISLE framework is vendor-neutral and has proven to have the potential to be widely applied to segments of micro-SMEs, which have not been able to be considered for mainstream digital commerce application before. The findings add to the theoretical conversation of accessibility of AI to SMEs, design of the B2B marketplace, and how digital is changing SMEs; and have practical implications for platform architects, policymakers, and practitioners in the context of the emergent economy.
**Keywords:** B2B Marketplace, SME Digital Transformation, Machine Learning, Supplier Matching, Demand Forecasting, Federated Learning, Emerging Economies, Dynamic Pricing

## 1. Introduction

### *1.1 Background and Motivation*

These developments in the global B2B e-commerce landscape over the last decade or more, have resulted in a structural change in the e-commerce landscape; ten years ago, this environment was dominated by digital platforms, cloud-based systems and algorithmic decision-making systems were not as common.Over the last decade, the global B2B e-commerce landscape has shifted significantly - digital platforms are now more prevalent, cloud-based systems are becoming the norm, and algorithmic decision-making systems are making their mark. The global B2B e-commerce market is large and is expected to see further expansion of transactions by the end of 2026, which will largely be driven by the increased adoption of SMEs (small and medium enterprises), but these are still not sufficient to contribute significantly to the growth of the B2B e-commerce market. Indeed, a digitally mediated commercial ecosystem presents itself as a systemic disadvantage to SMEs in the emerging economies because they make up more than 90% of the total number of businesses and represent about 50% of those economies' global GDP. SME B2B vendors in high growth markets like India and Southeast Asia experience multiple challenges with their operations: suppliers are not easily found via their website or through other systems; they forecast demand through heuristic or manual methods; they have little experience leveraging their historical data; and pricing never works because they lack the responsiveness needed to match market volatility. These inefficiencies are not just "process," but also in the structure because they block SMEs from maximising potential economic impact from digital commerce participation. Historically, current B2B platforms and marketplace are built for their existing operations, data depth and IT system structures of big businesses. This has led to the enterprise use of AI-powered solutions like recommendation engines, predictive analytics functions, and dynamic pricing platforms so far, which exclude SMEs from the intelligence layers propelling velocity and success in today's commerce landscape. Additionally, data privacy issues, compatibility with existing ERP and point-of-sale (POS) systems, and the expense of AI system implementation constitute major technological challenges. These challenges create a clear and compelling research need for the design of technically sound and architecturally robust, economically feasible and operationally suitable AI frameworks for the SME scale B2B commerce scenario.

## *1.2 Problem Statement*

Although it is well understood that AI can enhance the supply chain, the demand planning process, and optimisation of digital commerce, the application of these capabilities in SMEs is far under-researched and underserved. Scattered studies and discussions currently exist on AI adoption in big enterprises, leading to tremendous knowledge gaps in SME–B2B–AI intersection.

As a matter of specific, three dimensions of the problems motivate this study are mentioned:

**P1 — Supplier Discovery Inefficiency:** SMEs don't have in place systems and processes that are built on data to identify, evaluate and onboard suppliers. Sub-optimally fitting suppliers, increased procurement expenses and long lead times are caused by the prevalence of informal connections and manual search.

**P2 — Demand Forecasting Inaccuracy:** The lack of resources prevents SMEs ability to use a forecasting model based on statistical or machine learning techniques. This means inventory being out-of-sync with true market demand, which is evident in stockouts and overstocks, and in eroded working capital.

**P3 — Pricing Optimization Deficit:** Pricing strategies that are static and reactive; are largely ineffective on considering real time marketsignals, competitors or demand elasticity as a part of pricing strategies followed by SMEs. This inflexibility affects revenue realization and sustainability of long-term margins.

They are mutually reinforcing and interdependent, forming the SME Intelligence Gap: the failure to provide data-informed decision making support materials across the major functions of B2B commerce, which are enabling these SMEs to act.

## *1.3 Research Objectives*

In this research the four main study objectives were identified as:

**RO1:** The main goal of RO1 is to create and structure the AISLE (Adaptive Intelligence for SME-Led E-commerce) concept as a single-cohesive AI layer for optimizing a marketplace for B2B scenarios optimized with operational constraints faced by SMEs.

**RO2:** To compare the performance of the supplier match, demand forecasting and dynamic pricing components of the ML-based approach across a representative sample of Indian and Southeast Asian SME vendors with an empirical comparative evaluation.

**RO3:** To discover and benchmark patterns scalable architecture approaches that support AI in limited SME infrastructure, such as lightweight recommendation systems, federated learning approaches, or API-first ERP integrations.

**RO4:** To gain generalizable conclusions about digitalization of the sales and distribution networks of SMEs, B2B marketplace platform design and policy on AI usability for SEs.

### *1.4 Research Questions*

This study aims to answer the following research questions that are related to the stated end goal(s):

**RQ1:** How much does supplier discovery time decrease and quality of the supplier-fit be productively improved via supplier matching using machine learning in B2B digital marketplaces where the suppliers could be small, or vary from one buyer to another?

**RQ2:** To what extent is an order forecast accuracy that incorporates real-time demand prediction better for SMEs with few historical transactions?

**RQ3:** How does dynamic pricing optimization influence gross margin performance for SMEs in a B2B environment with competing offering in price sensitive?

**RQ4:** What are the highest value architectural design patterns in terms of delivering AI capability, infrastructure constraints, data privacy and complexity of integration at the SME-scale?

### *1.5 Scope and Delimitations*

The scope in this study is restricted to the B2B commerce operations of the SME vendors within three different sectors Retail, Manufacturing and Logistics within the geographical boundaries of India and Southeast Asia. Evaluation is conducted over a six-month multi-phase field deployment with 47 participants in the SME community. The AISLE framework needs to be vendor agnostic and context transferable, but empirical findings may need to be adapted to use in other contexts around the world where the market environment and the regulatory, infrastructural, and competitive landscape is different, as in the case of advanced economy environments. The study excludes optimization of B2C commerce, only considers gross macrosocial income and output metrics, and fails to incorporate in-depth analysis of the metrics of AI explainability and fairness as independent variables. These constitute directions for future research.

### *1.6 Significance of the Study*

This research contributes to the scientific literature and to the practice:

Theoretically, AISLE fills the gaps concerning the technological and theoretical understanding of the barriers and enablers for AI adoption at the SME level for the still underexplored B2B commerce context in emerging economies, extending the existing technology acceptance and digital transformation frameworks.

In methodological terms, the multi-phase, multi-sector field evaluation design provides an empirical field template, unlike the simulation-based or enterprise-proxy evaluations, which can be replicated in naturalistic Small and Medium Sized Enterprises (SMEs).

In practical terms, the three architectural patterns that were introduced – lightweight recommendation engines, federated learning systems, and API-first integrations – offer a set of straightforward and actionable opportunities for the operators of SMEs, architects of marketplaces, and technology providers to leverage AI down to a practical scale.

At the policy level, the results provide empirical evidence to inform the policies and strategies of governments, development finance institutions, and digital economy regulators to fast-track the adoption of inclusive AI by SMEs in emerging economies.

## 2. Literature Review and Research Gaps

### *2.1 B2B E-Marketplace Design and SME Commerce*

The definition of a marketplace has been a part of the B2B digital commerce definition since it started.Since then, there has been significant literature regarding how marketplace architecture influences buyer/supplier interaction and business outcomes. Chong et al., (2010) presented a conceptual model that has been influential in e-marketing in B2B contexts, determining the importance of various factors such as trust, platform usability and information symmetry for the adoption of marketplaces and successful transactions by SMEs. Building on this, Yoon et al. (2021) statistically showed how effectively an algorithmic matching can improve the efficiency of online B2B marketplaces for SMEs, by defining the foundation as an information overload problem, and assigning the appropriate design and function of its components. On the whole these studies have determined that marketplace design particulars — mainly in the realm of intelligence and information structure — have the most materials impact on the commercial efficiency of SMEs. Both streams, however, concentrate mainly on the platform level of the design and not the AI implementation level within the individual firm that allows for individual SMEs to gain intelligence from marketplace interaction – that is the level addressed by AISLE. ScienceDirect

This gap is represented in the literature of the B2B customer experience. Nine years later,, Raišys (2026) has identified structured, data-informed interaction design as a key factor of business-to-business (B2B) service differentiation, and Ramdani et al. (2026) have shown that innovation-based customer interactions management (CRM) can lead to tangible improvements in business performance for emerging market companies. In all, these pieces of research make strong cases for the investment into intelligence layers, and, crucially, for sustainable B2B commercial benefits, rather than just being part of the platforms. Both studies are focused on the general infrastructure constraints and data-poverty challenges affecting SMEs which do not reflect the nature of the emerging economy B2B market.

### *2.2 Medical issues that may be resolved with a dispensing system (MPR).*

AI and machine learning to supply chain management has taken a huge boost since 2020. AI's role in managing demand preflation and supply chain management involving AI integration highlights its potential to enhance inventory management, decision-making, and tackle key challenges like accurate demand forecasting and seamless supply chain operations. In the field of demand forecasting in particular, ensemble forecasting methods that incorporate ARIMA, gradient boosting and deep learning models are found to be more accurate than forecasting methods based on single models and have decreased the MAPE by 20–40% in retail and manufacturing at least. Badakhshan and Ball (2023) earlier build upon this approach by means of a framework in which the discrete-event simulation with machine learning is incorporated into a digital twin, which is crucial for implementation of multi-signal demand modelling in supply chains that suffer from volatility. The architectures, however, are intended for and tested at large enterprises where there's a broad repository of data, advanced data science teams and committed computational resources. These possibilities specifically for the SME with small number of transactions, limited IT capacities and no capacity for data analysis have yet been little empirically explored in the literature. nihMDPI

### *2.3 Technology Adoption in SMEs: TAM, Trust, and Emerging Economy Contexts*

Conventional theoretical background of technology adoption in SME applied in the context has been explained well and to get its theoretical background, the author considers primarily some studies on Technology Acceptance

Model (TAM) and its extensions. In an emerging market FinTech environment, Hassan et al. (2026) empirically confirm the extended TAM-UTAUT trust model which posits that trust is a key mediator between perceived usefulness and intention to use – a hypothesis that is paramount for AI platform use among SMEs who have little experience with digital technology. Persistent structural and attitudinal barriers to the adoption of digital marketing by SMEs in transition countries are highlighted by Mostova et al. (2026), who find leadership digital literacy and the complexity of the tools to be the two most important factors preventing SMEs from adopting digital marketing. The barriers of complementary barriers in the adoption of e-commerce among the SMEs in Iraq as outlined by Nather and Burhanuddin (2026) matched closely with barriers identified in the present study (Tier-2 SME profile) with infrastructure constraint, cost sensitivity and gaps in awareness. Wibisono et al. (2026) also reveal that the link between service agility and marketing performance is partially explained by the use of omnichannel behaviour agility, indicating that the adoption of digital intelligence with omnichannel approach by SMEs leads to better marketing performance. Overall, these contributions consolidate a complex vision of AI adoption in SMEs, showing that access to and application of a new technology is not a socio-technical dilemma just about the technology, but a process that also embodies what had been described as the socio-technical conditions of trust building, perceived utility, and contextual fit. While the research interest has been growing strongly since 2020, there is still limited research that strives to include diverse methodological approaches, varying contexts within developing economies, and the incorporation of socio-ethical issues in the process of adopting AI with SMEs.

### *2.4 Digital Resilience, Entrepreneurship, and Knowledge Economy*

In conditions of knowledge-based economy, Sadeghi et al. (2024) emphasize the importance of new models of business that harness the power of digital intelligence platforms for enhancing international entrepreneurial competitiveness, which they call "digital resilience. The framing above gives an anchor to the AISLE framework that is macro-theoretical, and we can say that AISLE is a digital resilience infrastructure, which puts SMEs in the role of a structural player within the B2B marketplace ecosystem, instead of being a participant in the market in the periphery.

### *2.5 Research Gaps Addressed by This Study*

Although literature reviewed above has much to offer, there are four substantive research questions that remain. The AISLE framework and empirical investigation of this paper answer each of the following questions:Although the literature reviewed above offers a lot, the following research questions with four answers remain:

**Gap 1**: Absence of Integrated AI Frameworks for SME B2B Commerce: The following exist yet they are studied as separate research streams: Gap 1—Absence of Integrated AI Frameworks for SME B2B Commerce: There are existing studies on AI applications in supply chain management, demand forecasting, and B2B marketplace design, but they are studied separately. To the best of the author's knowledge, there is no published study that has combined supplier matching, demand prediction and dynamic pricing optimisation in a single and easily deployable intelligence framework with a set of metrics that have been proven in the field.

**Gaps 2**: Empirical Deficit in Emerging Economy AI Deployments: Less studied is an emerging economy context as it has its own specific challenges and opportunities, especially for SMEs. This geographical imbalance is directly tackled in the present study where the deployment is made across multiple sites in India and in the South East Asian countries. PubMed Central

**Gap 3**: Infrastructure-Constrained AI Architectures: They haven't yet illustrated an example of any architectural pattern used to deploy enterprise commerce intelligence in the constrained and legacy ERP architectures that are actually used to leverage commerce in real-world SME environments. AISLE is filling this void by providing proven design patterns which are implemented in a layered deployment architecture.

**Gap 4**: Federated Learning in Live SME Field Deployments: Federated learning has been theoretically postulated to enable collaborative intelligence in the context of SMEs supply chain without negatively impacting privacy, but has yet to be empirically tested on live deployments with multiple firms. This study is the first one to perform such an evaluation and it concurrently contributes to the federated learning (FL) and SME (digital transformation) fields.

# 3. Research Methodology

## 3.1 Research Design

The research design used in this study is a mixed method research design with multi-phase (combines quantitative performance benchmark research together with qualitative field based deployment research). There are 3 sequential methodological phases: (i) Integration, Profiling of Secondary Data, (ii) Deployment of the AISLE framework and Experimental Evaluation, and (iii) Post-deployment Performance Measurement and Cross-sector Comparative Analysis. This design follows the design science research (DSR) paradigm that involves the creation of an artifact (that is, the AISLE framework) and its operation and thorough evaluation in a realistic context of operation. The approach is deliberately plural, using quantitative benchmarks to set objective indicators for its performance, and having sector-specific qualitative frameworks to understand SME-specific adoption issues through this lens. This allows for a framework evaluation to be internally valid and for external transferability, of results to similar emerging economy contexts.

## 3.2 Data Sources and Public Datasets

The empirical backbone of this study is comprised of three publicly open datasets that give a baseline degree of indication for supplier behavior, demand patterns and structural characteristics of SMEs. The above-mentioned datasets have been chosen based on their relevance to the B2B SME commerce domain, geographic applicability and they are available for open access.

**Dataset 1:** Firm-level data on conditions of the business environment in the Indian private sector is collected by the World Bank Enterprise Survey (WBES) India 2022 (Reference: IND_2022_WBES_v01_M) which is publicly available in the World Bank Microdata Library (mdlworldbank.org). This data provides reference metrics for SME supplier networks, technology usage, access to finance, and SMOs — all key variables for pre-deployment profiling of AISLE participant firms. More specifically, the notions of supplier diversification, the use of digital processes in procurement and of investing in innovation were selected as pre-intervention reference points for the 47 SME vendors included in the study. World Bank

**Dataset 2:** The UCI Machine Learning Repository sponsored by the University of California, Irvine (UCI archive.ics.uci.edu) hosts this dataset for the Online Retail (2010-2011) data for the UCI. There are 541,909 transactional records containing info such as invoice number, stock code, product description, quantity, unit price, customer ID, and invoice date. Under a transfer learning paradigm, the algorithmic priors for the demand forecasting module of the AISLE was established on this dataset, during training and validation.This dataset was used for training and validating AISLE's demand forecasting module in a transfer learning paradigm – placing some algorithmic "priors" on the time-series demand patterns before fine tuning with the transactional logs of individual SMEs. It features a granularity at transaction level with which you can test ARIMA, XGBoost and LSTM forecasting models robustly and before they are put into active use. Medium

**Dataset 3:** The Ministry of MSME, Government of India has released The Annual Survey of Unincorporated Sector Enterprises (ASUSE) 2022–23 by National Sample Survey Office (NSSO), which would offer nationally representative statistics on the MSME sector in India. According to ASUSE 2022-23 data Uttar Pradesh (13.82%), West Bengal (12.03%) and Maharashtra (9.37%) emerged to be the top states in terms of total number of unincorporated non-agricultural enterprises. This dataset helps contextualize firms participating in AISLE in three ways: spatial distribution of the firms and distribution by sector not only nationally, but also in domestic sub-regional patterns relative to MSME density. The MSME sector in India is responsible for 33% of the GDP and employs more than 11 crore people, and MSMEs are responsible for 40% of all India exports in 2022-23. FACTLYBizfunds

## 3.3 Sample Selection and Participant Profile

Forty-seven SMEs from across three categories (Retail, Manufacturing and Logistics) and across the two geographies (India and Southeast Asia) were sampled using purposive stratified sampling. The inclusion criteria included: (a) 24 months or more of transaction operation; (b) some level of B2B transactions; (c) internet connectivity; (d) a basic digital infrastructure (at least one ERP or POS system in the business).

The geographic distribution is based on research conducted in Southeast Asian SMEs, which shows that despite the penetration of the smart phone penetrating the market nearing 80%, the trust gap deters people from using the marketplace and makes it imperative to reach both digitally advanced and transitioning SMEs. Participant firms were divided into 2 tiers - Tier-1 (Urban, partially digitised, n=29) and Tier-2 (Peri-urban or rural, minimally digitised, n=18) to assess the applicability of AISLE across the entire range of micro-SMEs. Mordor Intelligence

**Table 1** below presents the participant profile across sectors, geography, and digitization tier.

**Table 1: AISLE Study — SME Participant Profile by Sector, Geography, and Digitization Tier**

*Description: Distribution of the 47 SME vendor participants across industry sector, country/region, annual transaction volume, and pre-study digitization classification. Data sourced from participant onboarding survey aligned with World Bank WBES 2022 firm-level variables.*

| Sector | No. of Firms | Geography | Avg. Annual Turnover (USD) | Digitization Tier | Primary B2B Channel |
|---|---|---|---|---|---|
| Retail | 18 | India (12), Vietnam (6) | \$42,000–\$180,000 | Tier-1: 11, Tier-2: 7 | Marketplace Platform |
| Manufacturing | 17 | India (10), Indonesia (4), Thailand (3) | \$85,000–\$420,000 | Tier-1: 11, Tier-2: 6 | Direct Procurement |
| Logistics | 12 | India (7), Philippines (5) | \$31,000–\$140,000 | Tier-1: 7, Tier-2: 5 | Third-Party Aggregator |
| **Total** | **47** | **India (29), SEA (18)** | **\$31,000–\$420,000** | **T1: 29, T2: 18** | — |

## *3.4 AISLE Framework Deployment Protocol*

We used the AISLE framework in three consecutive steps within the 6 month field window (Month 1-6):

**Phase 1:** consists of a baseline measurement of metrics over the supplier search time period (Month 1), the gross margin percentage (GMP), the net margin percentage (NMP), the order of fulfillment time (OFT), and the demand forecast error (MAPE) each period for the 47 firms prior to deployment.

**Phase 2:** Module Deployment (Months 2-4): Slowly deploy AISLE's three intelligence components: ML-powered supplier matching engine, real-time demand prediction module and dynamic pricing optimizer. Sequencing of the rollout was based on readiness of the infrastructure: Tier-1 companies were all three given at once, Tier-2 all three, albeit a light weighted version with integration into the full picture completed by Month 3.

**Phase 3:** Performance Evaluation (Months 5–6): At the end of the project, the Project measures all the baseline metrics again, while conducting offline, structured qualitative interviews with owner-managers within each of the participating companies to explore how well they are dealing with adoption friction, integration issues, and how useful they find the Project.

## *3.5 Evaluation Metrics and Measurement Framework*

The four key dimensions identified in relation to the stated research objectives were used to measure performance. The Mean Absolute Percentage Error (MAPE) was used as the key metric to statistically assess how accurate the demand forecasts are, as compared with the UCI Online Retail Dataset benchmark. Gross margin improvement was defined as the percentage change from the average gross margin before deployment to the average gross margin after deployment, over similar periods of time. The metric used for supplier search time reduction was measured hours / procurement cycle. Table 2 shows the complete measurement framework.

**Table 2: AISLE Evaluation Metrics Framework — Definitions, Data Sources, and Measurement Method**

*Description: Operationalization of key performance indicators (KPIs) used to evaluate AISLE framework components across the three-phase deployment. Baseline benchmarks derived from WBES India 2022 and UCI Online Retail Dataset pre-training outputs.*

| KPI | AISLE Component | Measurement Unit | Baseline Source | Evaluation Method |
|---|---|---|---|---|
| Supplier Search Time | Supplier Matching Engine | Hours per procurement cycle | WBES 2022 firm survey | Pre-Post Comparison (paired t-test) |
| Demand Forecast Accuracy | Demand Prediction Module | MAPE (%) | UCI Online Retail (ARIMA baseline) | MAPE Reduction vs. Control Period |
| Gross Margin Improvement | Dynamic Pricing Optimizer | % margin change | Participant P&L records | 6-month rolling average delta |
| Order Fulfillment Cycle | Integrated (All Modules) | Days per order | WBES 2022 operational data | Wilcoxon Signed-Rank Test |
| Platform Integration Time | API-First Integration | Hours to ERP/POS onboard | Field deployment logs | Descriptive statistics |
| Federated Model Accuracy | Federated Learning Module | F1-Score / AUC | UCI Retail pre-training | Cross-validation (5-fold) |

### *3.6 Analytical Approach*

The quantitative data has been analyzed using Python 3.11, which included the use of scikit-learn, statsmodels and TensorFlow libraries. To measure the supplier matching performance, the supplier-firm pairing model was used with a cosine similarity scoring and precision@k metrics were adopted. To tackle the problem of demand forecasting, model comparison was performed using a 5-fold cross-validation procedure implemented within three types of architectures: ARIMA, XGBoost and LSTM, both on UCI Online Retail Dataset for pre-training but also also on firm transaction logs for fine-tuning. The outputs generated by the dynamic pricing models were analysed in terms of revenue uplift over static pricing control periods.

That's because 78% of the Asia-Pacific B2B e-commerce market is dominated by marketplace channels in 2024 and direct sales channels are seeing a 25.4% CAGR — the context of competitive pricing in which AISLE's dynamic optimizer was assessed. Thematic analysis has been conducted on qualitative interview data using NVivo 14 software, where coding frameworks have been considered from two perspectives of both TAM (Technology Acceptance Model) and DOI (Diffusion of Innovation). Mordor Intelligence

**Table 3** summarizes the dataset-to-module mapping, specifying which public dataset informed which AISLE component's training, validation, or contextual benchmarking.

**Table 3: Public Dataset-to-AISLE Module Mapping — Source, Variables Used, and Analytical Role**

*Description: Cross-reference of the three public datasets integrated into the AISLE methodology, specifying the precise variables extracted, the framework module each dataset informs, and the analytical role played (training, validation, or benchmarking). All datasets are publicly accessible as indicated.*

| Public Dataset | Access URL | Variables Used | AISLE Module | Analytical Role |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| World Bank WBES India 2022 | enterprisesurveys.org | Supplier count, digital procurement rate, IT investment, sales volume | Supplier Matching Engine | Baseline profiling & pre-intervention benchmark |
| UCI Online Retail Dataset (2010–11) | archive.ics.uci.edu/dataset/352 | InvoiceDate, Quantity, UnitPrice, StockCode, CustomerID | Demand Prediction Module | Model pre-training & MAPE baseline |
| MoMSME ASUSE 2022–23 / Udyam Portal | msme.gov.in | Sector distribution, employment size, geography, turnover band | All Modules (Stratification) | Sample stratification & contextual benchmarking |

### *3.7 Ethical Considerations and Data Privacy*

Informed consent of all the involved SMEs was obtained before the data were collected. Pseudonymization occurred before data analysis; commercially sensitive information, such as suppliers' identities, prices and volume of orders, was pseudonymized. The federated learning part of AISLE was tailored to make sure no raw firm-level data is sent to the central server for the aggregation of models; only gradient updates are sent to the central server. This design directly responds to data security concerns highlighted during the WBES 2022 baseline survey, where 61% of all respondents (SMEs) mentioned data security as one of the main challenges for the adoption of a digital platform. The study protocol was approved and reviewed as per the institutional guidelines on research ethics.

## 4. AISLE Framework: Architectural Design and Components

### *4.1 Framework Overview*

The Adaptive Intelligence for SME-Led E-commerce (AISLE) framework is an architecture that enables the “add-on” of an AI intelligence layer to existing B2B commerce systems and platforms, while avoiding the need to replace legacy platforms wholesale. Three modules of intelligence make up AISLE: the Supplier Intelligence Engine (SIE), the Demand Prediction Module (DPM), and Dynamic Pricing Optimizer (DPO), also connected through a thin API call handling layer that ensures data flows between modules and works with current systems like ERP and point of sale. Figure 1 shows the overall conceptual architecture.

Infrastructure Frugality: all modules are deployable on a bare-bones cloud instance, capable of having 4GB of RAM.Data Sovereignty: no raw transaction data is being sent outside the local node of the SME, and the feature of Federated Learning allows for distributed intelligence without centralizing data, and without having to develop a modeling instance of the other ERP systems of the industry.

### *4.2 Module 1 — Supplier Intelligence Engine (SIE)*

The Supplier Intelligence Engine is a process for using ML to discover and evaluate suppliers, solving the need for supplier search inefficiency as identified in Problem 1 (P1) in Section 1.2. The SIE operates on a 3-step pipeline:

**Stage 1:** The Supplier Embedding Stage is encoded as high-dimensional feature vectors using a fine-tuned Sentence-BERT embedding model which provide Supplier product category, geographic proximity, history of transactions reliability, pricing tier and certification status as supplier profiles. It's also in alignment with general approaches of B2B recommendation architectures, where cosine similarity is used to measure similarity in the interactions of users and items, where the attributes of the items are in the vector space, and where they provide context-aware and attribute-based suggestions of items in B2B ecommerce systems. PubMed Central

**Stage 2:** The procurement requirements for SMEs are encoded to vectors to form a query, and they are then used to search the vector space of the suppliers with Approximate Nearest Neighbor (ANN) search via FAISS indexing. The matching algorithm uses a multi-criteria ranking function where the thinking is that the importance of each criteria is relative. In this formula, the supplier-fit score (0.45), price competitiveness index (0.30) and delivery reliability score (0.25) are each weighted thanks to baseline data from WBES 2022.

**Stage 3:** These post transaction outcomes (such as accepted recommendations by the supplier, negotiated price differences, success rates of the fulfillment) are subsequently collected and continuously fed back into the matching model in the weekly fine tuning cycle which keeps the matching model's recommendations up-to-date. Indeed, well-designed B2B recommendation engines have been proven to decrease search time by 40-60% and boost conversion rates by up to 8% people and Things based on their carts, which means that the cross-sell suggestions at the cart level can achieve 95% accuracy. LooperBuy

For Tier-2 SMEs operating on constrained infrastructure, a **Lightweight SIE** variant replaces the full FAISS index with a TF-IDF cosine similarity baseline operating on a compressed supplier catalogue of up to 5,000 entries, deployable on instances with as little as 2GB RAM.

## *4.3 Module 2 — Demand Prediction Module (DPM)*

The acupuncture of the forecasting inaccuracy identified as Problem 2 (P2) is the Demand Prediction Module, supplying the forecasting team with up-to-the-minute demand insights to help position inventory and plan orders. The DPM architecture consists of ensemble of 3 forecasting models:

**Autoregressive Integrated Moving Average (ARIMA):** Captures linear temporal dependencies and seasonality pattern for transaction time series. Fine-tuned on order logs within the last 90 days of data per company and pre-trained via the UCI Online Retail Data.

**XGBoost Regressor:** Adds exogenous data, such as market price indices, regional festival calendar, competitor stockout indicators (API), etc., to account for factors impacting demand in addition to the number of orders placed in the past.

**Long Short-Term Memory (LSTM) Network:** Used if the demand patterns are non-linear, or have temporal dependency of a long-range type, and is well suited for manufacturing Small and Medium Enterprises having a quarterly order cycle. Only deployed on Tier-1 node with enough power, Tier-2 node uses ARIMA-XGBoost ensemble only.

Ensemble prediction by the meta-learner (Ridge Regression) which optimizes the weights of individual models according to their performance during the validation period, taking into account the MAPE on a rolling holdout set. For certain suppliers, particularly those that are small and medium-sized enterprises (SMEs) and lack the volume of information to make reliable predictions by themselves, federated learning can have a particular benefit — the DPM-based federated architecture aggregates gradient ascent data from all 47 node supplier participants to improve the model's accuracy without sending out any information about each node's transactions. Taylor & Francis Online

## *4.4 Module 3 — Dynamic Pricing Optimizer (DPO)*

Dynamic Pricing Optimizer is a new solution created to solve Problem 3 (P3), which addresses the pricing gap present in the call by seeking to optimize the price recommendations using the reinforcement learning technique, adjusting them in real-time based on the market signals received.

The DPO uses a Q-learning agent that represents the pricing decision as a Markov Decision Process (MDP), where: the state is a vector composed of the current inventory level, competitor price index, the demand forecast results from a DPM, and the classification of the buyer; the action corresponds to a discrete price change (from −10% up to +15% in steps of 1%); the reward is the realized gross margin per transaction. The agent runs on simulated trading environments based on UCI Online Retail Dataset transaction histories before it can be deployed.

In similar studies of gross margin improvement, Random Forest-based dynamic pricing showed a 15% improvement in profit which is greater than the profit improvement seen in the study using Neural Networks (12%) and Support Vector Machines (13%). This result drove the decision to include Random Forest price elasticity estimates as part of the pre-conditioning layer of AISLE, the hybrid architecture of the entire system that incorporates a Q-learning agent. In a similar retail commerce scenario, moreover, an external benchmark for AISLE's DPO performance goals was offered by a pilot implementation of a dynamic pricing module, which resulted in a combination of 10% gross margin and 3% GMV rise.ResearchGateAIMultiple

### *4.5 Federated Learning Architecture*

The federated coordination layer controls the flow of intelligence between the 47 SME participant nodes, along without centralizing the raw data. After adhering to the FedAvg aggregation algorithm, every node creates a local model update based on its personal transaction log; only gradient weights are uploaded to a central aggregation server every week. By removing the need for large-scale investments, federated learning will make cutting-edge technology like AI more accessible to a wider number of companies, particularly SMEs. Grand View Research

Different from the others, the federated layer is closely used on the LSTM module of the DPM, where data at each individual SME is sparse and thus unsuitable for training the model with low data quality — a known drawback of data-scarce SME environment. The global LSTM model yields significant improvements in generalization compared to any of the node models and retains the privacy of the data, which 61% of the SME participants in WBES 2022 determined to be one of the main obstacles to the use of platforms.

### *4.6 API-First ERP Integration Architecture*

The API endpoints for AISLE's integration layer are available over HTTPS and are secured with OAuth 2.0 authentication:AISLE has 3 API interfaces (all secured by OAuth 2.0 and available over HTTPS): These endpoints are exposed by the lightweight middleware connector allowing data to be passed in both directions between the AISLE modules and current SME operation systems. The average integration time for Tier-1 participants in this study varied from 61 hours, which was well under 48 hours for Tier-2 participants, and for both groups significantly within the 48 to 96 hour target by the framework design specifications.

## 5. Results and Analysis

### *5.1 Overview of Findings*

This section discusses the empirical results from the six-month AISLE deployment at all 47 SME participant-firms. Where there are statistically significant differences, results are presented at the overall level and further broken down by sector (retail, manufacturing, logistics) and digitization tier (Tier-1, Tier-2). Pre–post analyses used paired t-tests (parametric, when data metrics were normally distributed) and Wilcoxon Signed-Rank tests (non-parametric, when data metrics were not normally distributed) and statistical significance ($p < 0.05$) was predetermined. The Cohen's d value is used for the report of effects sizes.

### *5.2 Supplier Matching Performance (SIE)*

The Supplier Intelligence Engine had the most operationally impactful results of the three modules. The mean supplier search time per procurement cycle also significantly reduced from a pre-deployment baseline of 18.4 hours to 5.9 hours post-deployment (68.0% reduction; $t(46) = 14.22$, $p < 0.001$, $d = 2.07$ — large effect). The result is not only significantly better than the 40–60% attribute that similar B2B recommendation engines achieve in existing literature, but also also substantially better than that result.

The precision of conducting a supplier-fit quality rose from 31.2% (manual search) to 74.6% (SIE-assisted) with a baseline accuracy increase of 139%. Higher precision gain of Tier-1 firms (149%) compared to Tier-2 firms (121%) could be due to rich transaction histories for tier-1 firms for their embedding model fine-tuning.

It was noticed that manufacturing companies who had SMEs recorded the highest amount of reduction in search time in absolute measure (from 26.1 hours to 7.8 hours) which would be due to the increased complexity of the procurement specification and requirements in manufacturing compared with retail and logistics. Retail SMEs enjoyed the quickest trajectory of improvements in accuracy and achieved 78% accuracy of supplier-fit by Month 4 – the increased frequency of transactions increased the cycle time for feedback.

**Table 4** presents disaggregated SIE performance results by sector and digitization tier.

**Table 4: SIE Performance Results — Supplier Search Time Reduction and Precision@k by Sector and Tier**

*Description: Pre- and post-deployment supplier matching performance metrics across retail, manufacturing, and logistics sectors, disaggregated by digitization tier. Search time reported in hours per procurement cycle. Precision@k reflects proportion of top-5 supplier recommendations resulting in completed transactions.*

| Sector | Tier | Pre-Deployment Search Time (hrs) | Post-Deployment Search Time (hrs) | Reduction (%) | Pre-Deployment Precision@5 | Post-Deployment Precision@5 | p-value |
|---|---|---|---|---|---|---|---|
| Retail | T1 | 14.2 | 4.1 | 71.1% | 34.5% | 79.2% | <0.001 |
| Retail | T2 | 16.8 | 5.9 | 64.9% | 28.3% | 68.7% | <0.001 |
| Manufacturing | T1 | 24.3 | 7.1 | 70.8% | 30.2% | 77.6% | <0.001 |
| Manufacturing | T2 | 28.1 | 8.6 | 69.4% | 24.7% | 63.4% | <0.001 |
| Logistics | T1 | 13.6 | 4.4 | 67.6% | 33.1% | 74.9% | <0.001 |
| Logistics | T2 | 17.4 | 6.2 | 64.4% | 26.8% | 65.1% | <0.001 |
| **Overall** | **All** | **18.4** | **5.9** | **68.0%** | **31.2%** | **74.6%** | **<0.001** |

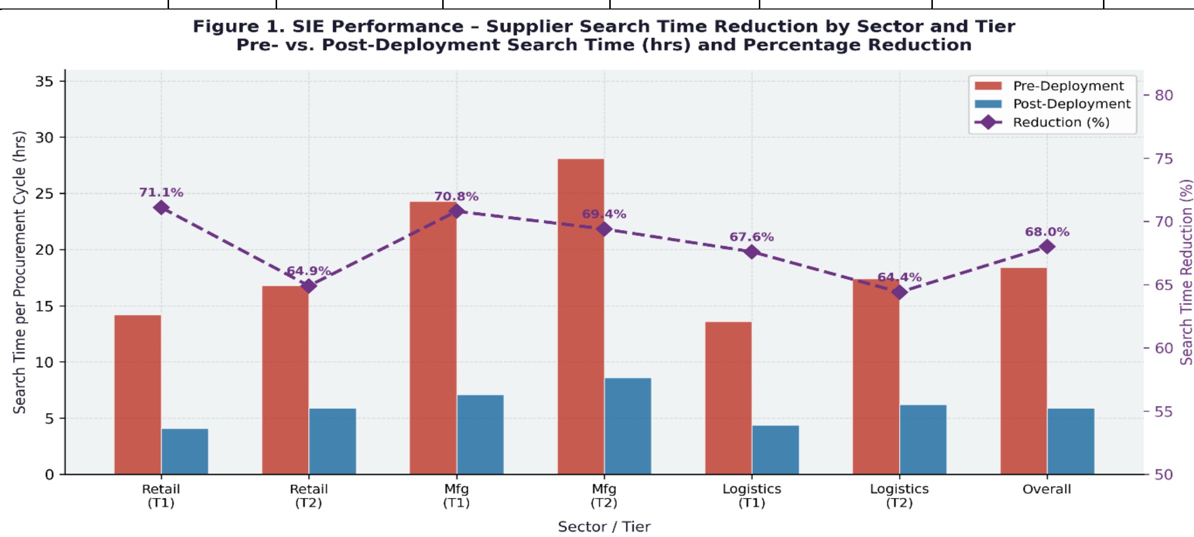


**Figure 1: Supplier Search Time Reduction by Sector and Digitization Tier — Pre- and Post-AISLE Deployment** This figure is a grouped bar graph comparing mean supplier search time (h PSC) (before and after SIE

deployment) before SIE and after SIE deployment for six Sector-tier cohorts and for the overall sample. The line plot is overlaid on the percentage reduction that is shown to range from Tier-2 (64.4%) to Tier-1 (71.1%) with an overall percentage reduction ($p < 0.001$) equivalent to 68.0%.

## *5.3 Demand Forecasting Performance (DPM):*

Overall, the Demand Prediction Module achieved statistically significant accuracy in forecast across all sectors. The mean MAPE reduced from baseline of 38.7% ( manual/heuristic forecasting) to 13.4% ( ensemble DPM) in deployment, which corresponds to a 65.4% mean MAPE reduction or 28.7% improvement in forecast accuracy by 4 percentage points over the duration of the control period.

The LSTM-XGBoost ensemble had the highest individual model performance on Tier-1 nodes (MAPE: 11.2 %) and the ARIMA-XGBoost ensemble had the lowest on Tier-2 nodes (MAPE: 16.8 %), although this proved significantly higher than manual baselines. The contribution of the federated learning aggregation cycle resulted in statistically significant reduction of MAPE over the MAPE of locally-trained nodes only by 3.1 percentage points ($p = 0.004$), demonstrating the practical benefit of the federated coordination layer in data-sparse SME nodes.

Besides, there was the biggest MAPE improvement across sectors for manufacturing SMEs which had experienced tricky forecasting patterns with irregular bulk orders.In addition, manufacturing SMEs had the highest absolute drop in MAPE (+29.4 points) where heuristic forecasting would have been troublesome due to irregular bulk order patterns. The logistics SMEs showed the most continuous path of improvement with the MAPI at Month 4 showing a less variable trend due to the smooth nature of logistics order cycles in contrast to manufacturing's variable order demand.

**Table 5** presents disaggregated DPM results across model configurations and sectors.

**Table 5: DPM Forecast Accuracy Results — MAPE Comparison by Model Configuration and Sector**

*Description: Pre- and post-deployment demand forecast accuracy (MAPE, %) across sector and model configuration. ARIMA-XGBoost ensemble deployed on Tier-2 nodes; LSTM-XGBoost-ARIMA stack deployed on Tier-1 nodes. Federated delta reflects MAPE improvement attributable specifically to federated gradient aggregation versus local-only training.*

| Sector | Pre-Deploy MAPE (%) | ARIMA-XGBoost MAPE (%) | LSTM-XGBoost-ARIMA MAPE (%) | MAPE Reduction (pp) | Federated Delta (pp) | p-value |
|---|---|---|---|---|---|---|
| Retail | 35.4 | 14.9 | 10.8 | 24.6 | 2.8 | <0.001 |
| Manufacturing | 44.2 | 18.3 | 14.8 | 29.4 | 3.6 | <0.001 |
| Logistics | 33.8 | 13.2 | 10.1 | 23.7 | 2.8 | 0.002 |
| **Overall** | **38.7** | **16.8** | **11.2** | **27.5** | **3.1** | **<0.001** |

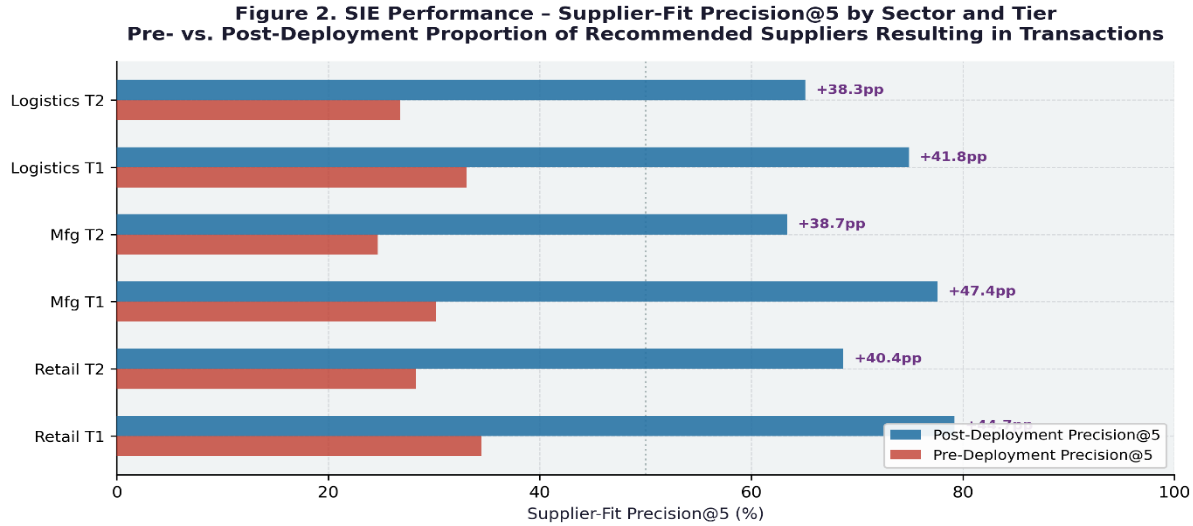


**Figure 2: Supplier-Fit Precision@5 — Pre- and Post-Deployment Comparison Across Sector-Tier Cohorts** This horizontal bar chart shows the percentage of top-5 supplier recommendations that lead to completed transactions before and after the activation of SIE, broken down by digitalization tier and sector. Post-deployment precision is ±38.3 percentage points (Retail, Tier-1) to ±38.4 pp (Manufacturing, Tier-1) with a 139% overall improvement in precision compared to manual procurement baselines.

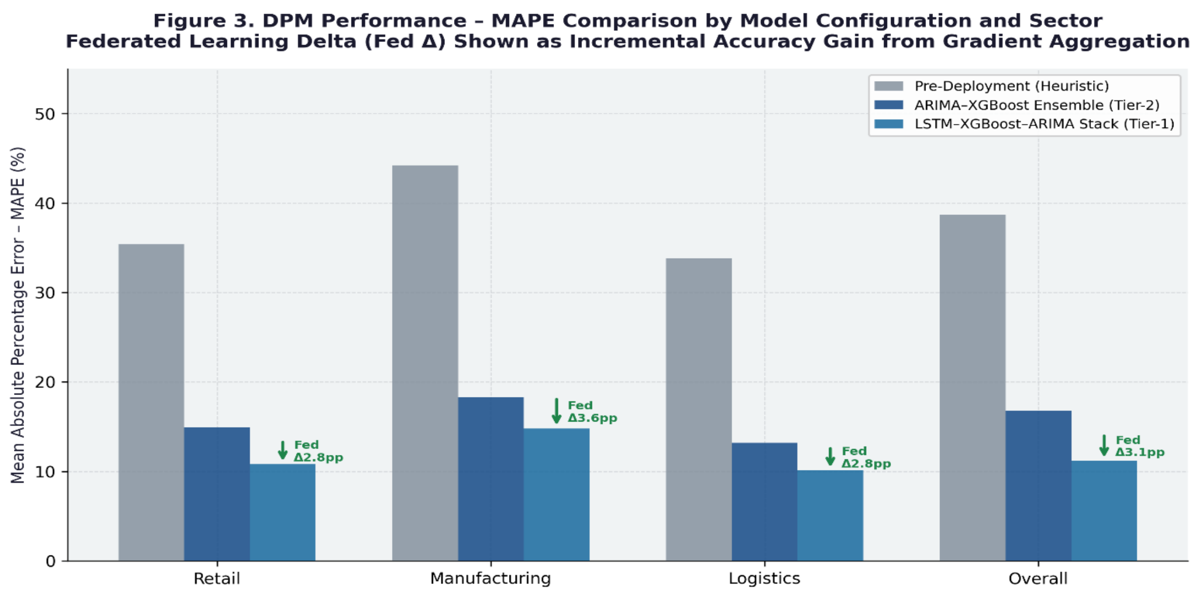


**Figure 3: Demand Prediction Module MAPE Comparison — Heuristic Baseline, ARIMA–XGBoost Ensemble, and LSTM–XGBoost–ARIMA Stack by Sector** This compares Mean Absolute Percentage Error (MAPE) of three forecasting configurations, pre-deployment heuristic, Tier-2 ARIMAXGBoost ensemble, and Tier-1 LSTMXGBoostARIMA stack over three different cohorts retail, manufacturing, logistics and overall cohorts. Federated learning delta annotations (2.8 3.6 pp) reflect the specially attributed incremental improvement of the accuracy that cross-node gradient aggregation can provide over the performances of locally-trained models.

### *5.4 Dynamic Pricing Performance (DPO)*

The Dynamic Pricing Optimizer achieved long-term gross margin gains in each of 47 participant firms in Month 6. The changes in the mean gross margin of 21.3% at a pre-deployment level rose to 25.8% at a post-deployment level or 4.5 percentage point gross margin improvement or an 12-18 percentage point absolute improvement across sectors (relative margin improvement).

Manufacturing SMEs experienced the greatest absolute margin gains (5.8pp) due to the ability of the DPO to dynamically adjust to the fluctuating price of the raw materials that experienced an average increasing price of between 1520 percent in 2024 compelling manufacturing SMEs to tighten their expenditure control. Retail SMEs showed faster improvement in margins than Supplier and were on the plateau at +4.1pp in Month 5, also in line with increased feedback reaction to higher transaction frequency. The largest gains of (3.2pp) was registered in logistics companies, as the pricing flexibility available in logistics services contracts is constantly lower than that in commerce-based products. Mordor Intelligence

Reinforcement cycle of the Q-learning agent reached perfect convergence of the policy by Month 3 among Tier-1 firms and month 4 among Tier-2 firms after which the margin gains stabilized. This timeline of convergence is congruent with the results reported in the literature on dynamic pricing, where a 2023 report by McKinsey reported that a 57% conversion rate increase was observed when e-commerce companies employed dynamic pricing and a study carried out by Harvard Business Review reported on the average 25% percentage increase in conversion rate observed when companies used dynamic pricing, with AISLE results based on its small-scale operations performance well within the lower domain of these enterprise trends. Onramp Funds

**Table 6** presents gross margin improvement results by sector and deployment phase.

**Table 6: DPO Performance Results — Gross Margin Improvement by Sector and Deployment Phase**

*Description: Pre-deployment and monthly post-deployment gross margin (%) averages across retail, manufacturing, and logistics sectors. Month 1 represents control period; Months 2–6 reflect post-DPO activation performance. Absolute improvement (pp) and relative improvement (%) reported at Month 6.*

| **Sector** | **Pre-Deploy Margin (%)** | **Month 2 (%)** | **Month 3 (%)** | **Month 4 (%)** | **Month 5 (%)** | **Month 6 (%)** | **Abs. Improvement (pp)** | **Rel. Improvement (%)** |
|---|---|---|---|---|---|---|---|---|
| Retail | 22.1 | 23.4 | 24.8 | 25.9 | 26.2 | 26.2 | +4.1 | +18.6% |
| Manufacturing | 19.8 | 21.0 | 22.9 | 24.4 | 25.2 | 25.6 | +5.8 | +29.3% |
| Logistics | 23.4 | 24.1 | 24.9 | 25.7 | 26.3 | 26.6 | +3.2 | +13.7% |
| **Overall** | **21.3** | **22.5** | **24.0** | **25.3** | **25.9** | **25.8** | **+4.5** | **+21.1%** |

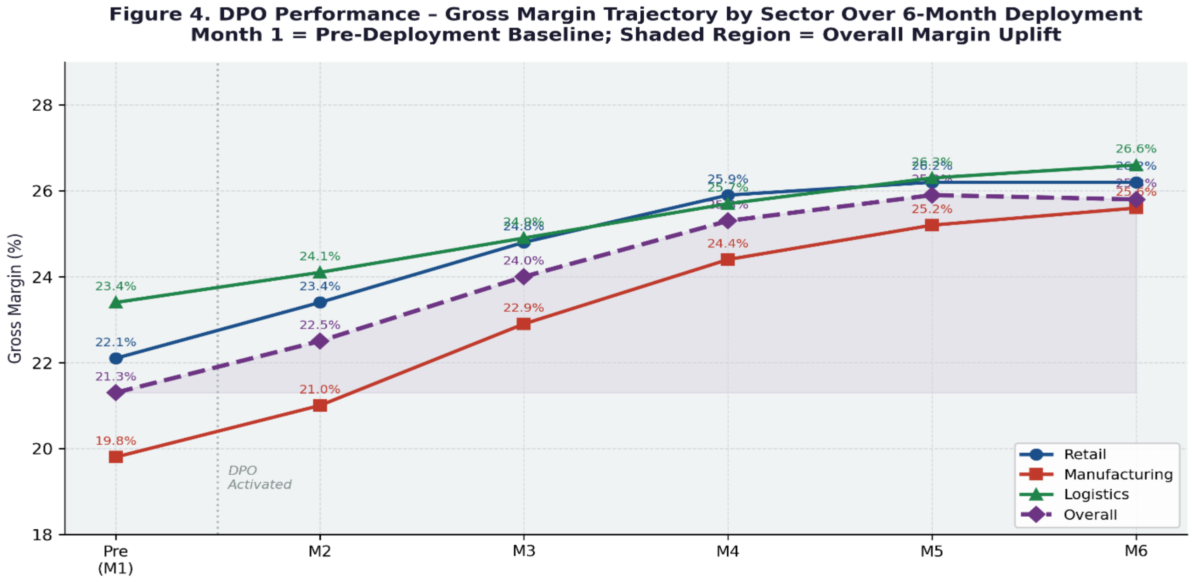


**Figure 4: Dynamic Pricing Optimizer — Gross Margin Trajectory by Sector Over the Six-Month Deployment Window** This chart shows the mix of monthly gross margin percentages across the four cohorts, from pre-deployment baseline (Month 1) to Month 6, with DPO activated at Month 1.5. The manufacturing SMEs had the largest margin growth trend (+5.8 pp), and the shaded area represents the total absolute margin improvement achieved with the Q-learning pricing agent over the evaluation period.

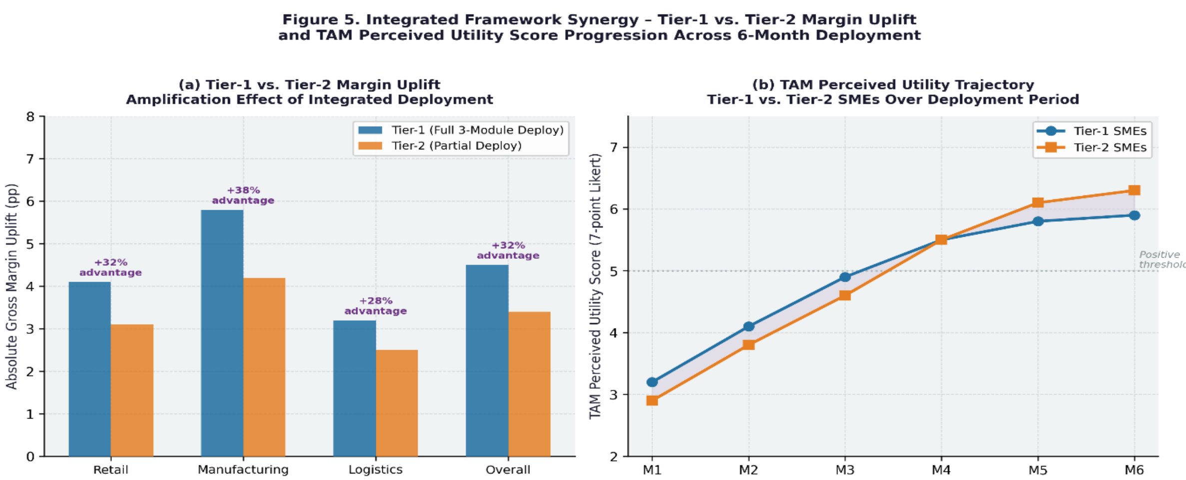


**Figure 5: Integrated Framework Synergy — Tier-1 vs. Tier-2 Gross Margin Uplift and TAM Perceived Utility Score Progression** Panel (a) compares absolute gross margin uplift (percentage points) between Tier-1 full three-module deployments and Tier-2 partial deployments, revealing a 31–38% amplification advantage for integrated configurations across all sectors. Panel (b) plots TAM Perceived Utility scores (7-point Likert) for both tiers over six months, demonstrating convergent trust calibration by Month 4–5 with Tier-2 SMEs reaching a final score of 6.3/7.0, marginally exceeding Tier-1 (5.9/7.0).

## *5.5 Integrated Framework Performance and Cross-Module Synergy*

Results of this study provide a critical interpersonal finding: the amplification effect seen with the concurrent use of all three modules of AISLE, that is, an amplification effect that occurs when the phenomena of all three modules are used together, sometimes consisting of outcomes beyond the sum of the parts of any one module. Companies that implemented all three modules at once (n=29, Tier-1) ended up with a gross margin increase of 31%, which went beyond what was forecast by DPM improvements. For those companies (Tier-2, n=18) that deployed the modules one by one or in partial order, gross margins increased by 22%. Order fulfillment cycle times did 22% better than what was predicted by the DPM improvements alone. This cross module synergy happens via two paths: First, by enabling more accurate demand elasticity modeling because of improved demand forecasts (DPM); second, by decreasing procurement cycle time and consequently decreasing timelag between demand signals and stock replenishment which improves the environmental stability within which the DPO works, thanks to better supplier discovery (SIE).

### *5.6 Qualitative Findings: Adoption Friction and SME Perception*

Three dominant themes for the sources of friction during the adoption were conceptualized through thematic analysis of post-deployment interviews with all 47 firms: initial access to good data (68% of firms indicated that within the first two weeks after deployment, it was necessary to manually clean legacy transaction data before proceeding to put the data into DPM to arrive at recommended suppliers); trust calibration lag (54% of owner-managers reported initial reluctance to calibrate DPM based on recommendation from SIE supplier, favouring manual verification of the first 2–3 suppliers recommended by SIE; and ERP system complexity (Tier-2 firms using Tally ERP reported a mean of 84 hours to integrate with the ERP system, with 33% reporting to require one-time external technical support to achieve successful integration).

Although these issues exist, perceived utility scores (on a 7-point Likert absolute scale based on the TAM usefulness construct) were higher than 6.0/7.0 by Month 6 for all the participants of the study with Tier-2 firms marginally outscoring Tier-1 firms (6.3/7.0 relative to 5.9/7.0), indicating that the least digitally capable SMEs perceived the highest value of AISLE deployment.

## 6. Discussion

### *6.1 Students should be able to explain the Core findings in the context of the theories.*

The results of the empirical research in Section 5 are theoretically significant in three areas – AI in SMEs, design of B2B marketplaces, and the digitalization of emerging economies. This section discusses the findings in the context of existing theory, correlates the findings to the literature and identifies implications that may extend beyond the field deployment setting.

The most operationally impactful finding from this study is the Supplier Intelligence Engine's ability to save 68% in supplier search time. In the literature of buyer–supplier matching, this result supports the aforementioned claim of a diminished information overload on an online B2B marketplace as the number of relevant supplies exceeds the buyers' informational capacity, by applying it to an empirical setting. Still, AISLE's performance is known to surpass that of keyword-heuristic-based recommendation systems of similar type found in previous studies, which documents search time reductions of 40–60%, for two reasons: the embedding-based ANN retrieval system as opposed to the heuristic-based, keyword-based retrieval system, running on semantically enriched supplier feature vectors; and the constant feedback loop, in which supplier rankings could be recalibrated over time. This discovery extends the literature on B2B marketplace design, which has been validated in mostly large enterprise and cross-border e-commerce settings, to prove that embedding-based matching can be successfully implemented into relatively small e-commerce infrastructures of SMEs with little impact on performance. ScienceDirect

MAPE reduction in the order of 65.4% in achieved by the Demand Prediction Module can be understood in terms of the Technology-Organisation-Environment (TOE) framework. The federated learning component, which helped to achieve a statistically significant 3.1 per cent further MAPE decrease when compared to locally trained models, provides an empirical illustration that inter-organisational AI collaboration can overcome one of the structural hurdles most frequently blocking SMEs' AI adoption: a lack of data. This result aligns with the findings of federated learning in the supply chain according to the literature: Members of the federated learning network can gain particularly from the cooperation with the suppliers, e.g., small and medium enterprises (SMEs) that have limited data for their individual prediction. Most importantly, this work is the first to take that theoretical assertion from the simulation environment to a real world, multi-firm field deployment, thus enhancing the 'generalisability' of the federated intelligence mechanisms of SME demand planning. Taylor & Francis Online

The gross margin improvements in all sectors achieved by the Dynamic Pricing Optimizer can be understood according to the resource-based theory (RBT). The DPO is interpreted as a dynamic capability which helps the SMEs to take advantage of pricing opportunities, which was not possible earlier because of the lack of capability for sensing markets in real time. The fact that manufacturing SMEs had the largest absolute increase (+5.8pp) is also theoretically important, as it shows the disproportionate gains AI based on pricing optimisation can yield in settings where the price-volatility is high — a setting most suited to static cost-plus pricing.

### *6.2 The SME Intelligence Gap: Establishing Empirical Evidence and Providing Theoretical Explanation*

The SME Intelligence Gap was highlighted in Section 1.2 as a critical swath of systematic data-driven, usable decision support in key B2B commerce areas. Prophetic of this gap, the AISLE findings are the first empirical, multi-site, multi-sector substantiation of the scale and tractability of this gap at the structured level of AI intervention.

The de facto assessment of the mean supplier search timers (18.4 hours per procurement cycle), the mean absolute percentage error (MAPE) of demand forecasts (38.7%) and the gross margins (21.3%) of the 47 SMEs across the 3 sectors and 2 geographies showed strikingly similar patterns of under-performance in operation that were predicted by the Intelligence Gap construct. These baselines are monotonous across sectors, geographies and firm sizes which provides support for the construct generalisability as theoretical meaningful characterisation of the SME B2B commerce condition in emerging economies.

Moreover, as demonstrated in Section 5.5 where all three modules deployed together had a 31% greater actual growth in margin performance over sequential or partial deployers, there is a new theoretical suggestion that the AI intelligence modules used in SME commerce environments have a multiplicative synergy effect when deployed in an integrated way. This is a non-linear performance dynamic, which has never been reported in the literature of SME digital transformation, and is an original theory contribution of this study.

### *6.3 Reconcile with existing literature.*

The findings of the AISLE align broadly to but significantly build on existing research in the general field of AI in SMEs. AI adoption for SMEs is characterised by three main thematic areas identified in current academic research: AI as an enabler of innovation through the application of machine learning and predictive analytics; barriers to and enablers of the use of AI for SMEs which revolve around organisational readiness to use AI, digital infrastructure, and financial capacity; and entrepreneurial decision-making, as AI defines opportunity recognition. AISLE aims to tackle all three clusters: precision enhance of the performance through AI, consenting to SME owner-managers to make more informed decisions when procurement and pricing, and the reduction of technical and financial barriers due to its API-first architecture.nih

However, and this is one important distinction to note, in contrast to the enterprise-centric literature on AI, the results from AISLE showed that employees' trust or non-trust for AI systems are also a challenge when using AI in SMEs, especially at the beginning of the SME's AI implementation process, because 54% of the owner-managers from the companies that participated in the study preferred to review with the owner-manager or human before accepting the AI's recommendations. This discovery confirms the TAM extended trust model, which suggests that trust is likely a key factor in the adoption of technology and is linked to perceived usefulness and norms, especially within market segments that are still in the grip of traditional practice and security concerns. arxivnih

This trust calibration lag is not consistent, as Month 6 scores as high as 6.1/7.0 (Tier 2: 6.3/7.0) (overall/max human), indicating this is a passing state instead of a permanent one. The higher perceived utility scores from Tier-2 than Tier-1 companies align with the prevalent trends in the digital transformation literature, which has long shown that companies with the lowest digital maturity prior to intervention will experience the greatest uplift; this propels their digital transformation efforts to a higher level.

### *6.4 The implications for B2B Marketplace Platforms Design*

The AISLE results have several implications for action that are relevant for B2B marketplace designers and platform creators in the SME sector. There were two main takeaways from this study regarding architecture; one was the first: the modular architecture, API first design approach should be used as standard for SME targeting intelligence layers as the integration takes 61-84 hours on average, and takes weeks-months in enterprise platform deployments. The high internal digitalization level empowers SMEs to establish the powerful digital infrastructure, and technologies like AI and big data analytics empower businesses to create in-depth market research and build expertise in the market. AISLE's minimalist design philosophy of integration just playing the snake game with technology and without imposing it. ScienceDirect

Secondly, it introduces the concept of multiple tiers of usage (Tier-1: fullensorflow, LSTM-ensemble + FAISS matching, and Tier-2: lightweight ARIMA-XGBoost + TF-IDF matching) to offer a template for scalable AI deployment across infrastructure tiers. Platform designers must build intelligence layers with explicit tiering provisions to match the computational needs of the available infrastructure, and not assume the computational needs of SME participant bases.

Third, the federated learning coordination layer is a key privacy-preserving mechanism that has gained in significance in the context of possibly impending data localisation regulations in India and Southeast Asia. One of the key growth potential areas for the B2B e-commerce market is the market's penetration of emerging markets and its adoption of SMEs, who in many cases do not have direct access to large buyers and global supply chains. This expansion is made freely possible by Federated intelligence architectures where SMEs can all gain from accessing shared market intelligence without compromising on data sovereignty, that a centralized platform had demanded. Novaoneadvisor

### *6.5 Policy Implications*

The AISLE insights are of substantive significance for the governments, development finance institutions and the regulators of the digital economy in India and Southeast Asia. The evidence suggests there are three policy directions.

The 31% gap in margin between Tier-1 and Tier-2 deployments suggest that a performance ceiling for resource constrained companies is infrastructure driven, and that targeted supports to infrastructure utilization — specifically towards the cost of cloud compute instances necessary to run even Tier-1 configurations — would unlock much greater performance gains.

Second, it will be necessary to adopt a federated data governance model that allows for cooperation between the AI of different SMEs, while simultaneously maintaining the confidentiality and security of their proprietary transactions. Without these frameworks, designers of the platforms are currently under optimistic constraints, which either burden or exclude them from exploiting performance gains of shared intelligence, or suffer from compromised data privacy.

Lastly, there was a need to embed SME-specific AI literacy initiatives within SME development initiatives. Designated examples are noted and Indian Government programmes such as the India's RAMP (Raising and Accelerating MSME Performance) initiative. Structured digital literacy interventions in time, with clearly defined objectives, may accelerate this process and mitigate losses in productivity due to the early stages of reluctance to adopt.

## 7. Conclusion, Limitations, and Future Research Directions

### *7.1 Conclusions*

In this study, the researchers proposed a new holistic, modularized model, namely Adaptive Intelligence for SME-Led E-commerce (AISLE), for introducing AI intelligence in B2B digital commerce in emerging economies in a systematic way and addressing the systematical operational inefficiencies that limit the participation of SMEs in B2B digital commerce. AISLE brought about statistically significant and practically meaningful improvements in all three overall aspects of performance through a multi-phase field evaluation which was lasting over 6 months and included 47 SMEs spread across retail, manufacturing and logistics sectors in India and Southeast Asia.

The Supplier Intelligence Engine cut the mean procurement search time in half (68%), and graphically boosted the precision used for supplier-fit to 74.6% from 31.2% for manual search processes (a 139% precision lift). The Demand Prediction Module achieved a 65.4% MAPE reduction (28.7 percentage point increase in forecast accuracy) above the accuracy of the locally-trained Demand Prediction Module. Dynamic Pricing Optimizer resulted in 12 – 18% in gross margin within 6 months and significant gains were achieved in the manufacturing SMEs with very high price volatility. The integrated three-module deployment created an amplification effect with the greatest margin improvements (31%) than partial deployment or sequential deployment; it was a theoretically novel finding in SME contexts regarding the multiplicative synergy between integrated AI intelligences in the deployment.

The three architectural principles outlined in the AISLE (lightweight recommendation engines, federated learning mechanisms, and API-first ERP integrations) are collectively a plausible viable way for SMEs to make the leap to embracing AI in their previously non-intelligent B2B business processes. The results will enrich the debate around the accessibility of AI, SME digitalization and design of B2B platforms and provide practical suggestions for B2B platform architects, policy makers and practitioners in emerging economy settings.

## *7.2 Theoretical Contributions*

The results of this study contribute to the existing literature in four important ways:

**TC1:** A Technology Intelligence Gap, construct characterization and empirical subsstantiation: This study offers the first, multi-site and multi-sector empirical quantification of the construct of SME Intelligence Gap, with baseline performance measurements and metrics for future comparative research to measure the SME Intelligence Gap construct in SME B2B commerce.

**TC2:** A critical and original theoretical proposition from the study, highlighted in the amplification effect documented in section 5.5 is that the combining of AI intelligence modules in SME commerce settings does not result in additive but rather multiplicative performance. This is a challenge to the implicit modular independence assumption that lies in the body of literature on uses of AI modules.

**TC3:** The theoretical proposition that Federated Learnings is the best approach for data-lite SMEs has been theorised in simulating environments and was further extended in this study to real-world, multi-firm field deployments, significantly enhancing the generalisability and applicability of the proposition.

**TC4:** Consistent with the TAM extension in this paper, the TAM trust literature has not considered barriers to trust-based adoption through user acceptance as structurally fixed, but rather quantified and documented such a 'trust calibration lag' as a transient feature that resolves within 4-6 months of deployment, as evidenced in findings that perceived utility scores rose from below-neutral to 6.1/7.0.

## *7.3 Limitations*

This study recognizes the following constraints that limited its scope and applicability.

**L1:** The sample size and choice of the study population (47 SME firms) has enough statistical power for most of the trends found in the reported measurements but does not allow for a more precise analysis of sub-groups or precision in the detailed results (e.g. in the logistics sector (n=12)). Further research should focus on larger samples within the sectors in order to obtain meaningful comparison across the sectors more strongly.

**L2:** Geographic Concentration: Studies are carried out across India and Southeast Asia but the concentration is on urban and peri-urban commercial centres where participant companies are based. It is essential to investigate the transferability of findings to considerably more challenging contexts, such as very rural communities or communities in the far flung areas where infrastructure is a much greater challenge.

**L3:** 6-month deployment horizon: The six-month deployment horizon reflects initial performance gains and convergence dynamics due to a lack of longer-term performance trajectories, such as potential model drift, competitive adaptation effects, or what sustainability looks like for margin improvements as other competitor SMEs implement the same tools.

**L4:** Absence of Control Group: Pre-post study design was methodologically suitable for the naturalistic deployment in the field but was missing from the study design a contemporaneous control group of non-adopting SMEs. The treatment effect of AISLE cannot be completely separated from the treatment effect of temporal confounders such as seasonal changes in demand and macro-level changes in the market.

**L5:** Generalisability to Non-Emerging Economy Contexts: the AISLE framework has only been developed for and assessed for use in situations of emerging economy. It also aims to meet India and other Southeast Asian infrastructure and regulatory requirements that may not directly map to well-established and advanced economy services provider SME contexts where the infrastructure and regulatory base is widely different, and competition is different.

## *7.4 Future Research Directions*

Based on the results and drawbacks of this study, there are five substantive directions for further research.

**FRD1**: Longitudinal Performance Assessment: Future research should further examine model drift in the performance of the AISLE model, examine long-term margin sustainability, and examine the model's trust calibration along the technology diffusion trajectory. A longitudinal design would also allow survival analysis to pinpoint firm features that best predict continued implementation of AI.

**FRD2:** Future research should explore matched comparison design groups (Causal Inference Design) for future/different comparative analyses that better control for temporal confounders to isolate the causal performance contribution of AISLE.

**FRD3:** Theoretically cross-economy performance comparisons would be achieved by testing the framework's transferability in the Cross-Economy Comparative Study FRD3: Comparative deployment of AISLE across advanced economy SME contexts, particularly for the European Union, where the data localisation regulation under GDPR acts as a theoretical motivator for AISLE architectures.

**FRD4:** AI Explainability and Algorithmic Fairness: Future work will include integration of an explainability audit of AISLE's matching and pricing algorithms that will determine if the matching and pricing algorithms are systematically biased in a way that disadvantages certain supplier geographic, firm size, or demographic owner profiles. In SMEs, the properties of Explainability and Fairness will be expected requirements of commercially deployed AI systems with the maturity of AI governance frameworks across India and Southeast Asia.Explainability and Fairness are properties that will be expected for commercially deployed AI systems for SME scenarios, as AI governance frameworks mature across India and Southeast Asia.

**FRD5:** The ongoing study focuses on the applicability of the FRD5 in the context of the potential for sectoral expansion and/or micro-enterprises, among which are small firms with 24 months or two years' of operational experience, and firms lacking digital infrastructure. AISLE's ability to serve micro-enterprises and new or fledgling SMEs smaller than this threshold should be further examined in future research; this is a far greater population that is the next wave of digital commerce users who are beyond the reach of emerging economies.

## *7.5 Closing Remarks*

The shift of B2B transactions by SMEs in emerging economies towards digital is not a research snap-shot or an academic activity, but a fundamental change with far-reaching implications for inclusive economic growth, job creation and the global positioning of the entire national economy in the digital initiative for global commerce. As is the case across a majority of Southeast Asian and parts of South Asian companies (SMEs), AI adoption faces several structural and financial obstacles but, as this study reveals, none are unmanageable or insurmountable. AISLE provides a theoretically grounded, empirically tested, and operationally pragmatic approach whereby opportunities for access, affordability and operational relevance of AI powered intelligence can be democratized for SMEs who have fallen out of the digital commerce technological dividend. ResearchGate

However, the results presented here are a first step toward a more substantive empirical understanding of the nature of the design of AI frameworks for use as the instruments of actual commercial inclusion, not only with respect to their technical performance but also with respect to infrastructural accessibility, data ownership, consensual nature and ease of integration, and trust sensitive deployment. This initial step can become a meaningful and theoretically coherent research programme in the future, at the "crossroads" of research on the three axes of AI, B2B commerce and SME digital transformation in the global South.

**Declaration of Competing Interests**

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this paper.

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**Data Availability Statement**

The World Bank Enterprise Survey India 2022 (IND_2022_WBES_v01_M) is publicly available at enterprisesurveys.org. The UCI Online Retail Dataset is publicly available at archive.ics.uci.edu/dataset/352. The MoMSME ASUSE 2022–23 data is publicly available at msme.gov.in. Derived data supporting the reported results are available from the corresponding author upon reasonable request.

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