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DIGITAL SUPPLIER TRUST SCORES: A NOVEL ERP-BASED FRAMEWORK FOR QUANTIFYING HIDDEN PROCUREMENT RISKS IN GEOPOLITICALLY VOLATILE MARKETS

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Abstract

Global procurement operations increasingly face risks that conventional supplier evaluation methods cannot detect in time. This paper proposes a Digital Supplier Trust Score (DSTS) framework that integrates Enterprise Resource Planning (ERP) data with machine learning classification, fuzzy multi-criteria decision analysis, and real-time sentiment signals extracted from open-source media. The DSTS assigns each supplier a composite numerical score that reflects operational performance, geopolitical exposure, sustainability compliance, and digital maturity. Two illustrative scoring tables and three mathematical formulations accompany the framework description. The paper argues that trust in supplier relationships is not a soft, qualitative attribute rather it is a computable, auditable variable that ERP systems can track continuously.
Index Terms – Supply Chain, ERP, Geopolitical, Digital

I. INTRODUCTION

Disruptions in supply chains not only served as logistical inconvenience but they also brought manufacturing lines to a standstill. Spiking prices and risks in procurement teams have never been formally modeled [12]. The issue is that the majority of supplier assessment systems are backward-looking. They rate the suppliers based on their previous delivery histories, audits of quality history and previous pricing conferences.

In this paper, a different approach is argued. The trust of suppliers should be a dynamic variable. It must integrate internal ERP transaction data and external geopolitical (and other) signals, sustainability and digital capability measures. This produces an Supplier Trust Score that is a single score that is easily interpretable and can be called upon by score procurement managers to take action before a disruption really occurs.

Researchers demonstrated that organisations that had their management systems certified like ISO 9001, ISO 14001, OHSA 18001, took their supplier risk seriously as compared to others [1]. However, certified companies are yet to have a harmonized computing device that converts risk indicators to easily comprehensible scores. Research proved that machine learning-based supplier ranking requires little or no additional work on SAP ERP systems as most of their raw transactional processing includes the necessary supplier ranking to achieve a classification accuracy of over 98% when applied to decision tree and support vector machine algorithms [4].

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II. BACKGROUND AND RELATED WORK

There are two levels on which Supplier risk research has evolved. The proposed track employs multi-criteria decision analysis (MCDA) to rank suppliers prior to the decisions. The second track is followed by continual monitoring following the selection.

Researchers came up with a Fuzzy Extended Analytic Hierarchy Process (FEAHP) which is an automated supplier ranking through weighted priority scores of hierarchically ranked ranking criteria [2]. A case of Brazilians oil and gas was dealt with in the system, with various suppliers and sensitivity analysis was used to ascertain that results were robust. Here, Shannon entropy weighting was used in combination with the fuzzy TOPSIS, with the demand risk being found as the most important one when selecting a spare parts supplier [10]. Other studies have further modelled uncertainty using trapezoidal intuitionistic fuzzy numbers (TrIFNs) and have employed the ELECTRE TRI-C sorting which is a method that not only ranks suppliers but categorises them according to discrete risk levels [3]. 20 suppliers based on 27 criteria. Two proved to be considered as being low risk indeed. It is important to have such a resolution.

Research revealed that supplementary information (textual) in both news media and twitter is effective in identifying risks within the supply chain before they lead to apparent disturbances [7]. They have used Latent Dirichlet Allocation (LDA) to derive risk topics using the COVID-19 Omicron wave and at the Ukraine-Russia war at the end of 2021 and the beginning of 2022. Identified risks were then measured in an ordered probit model to be able to perform sentiment analysis. Text data sources record risk indicators until the actual occurrences have fully developed. Such a variety of early-warning input is just the kind of input a trust score system requires.

The supplier trust discussion has also had an influx of blockchain. Research indicated that blockchain can improve cognitive as well as institution-based trust among partners in a supply chain whilst they did not find technology had an influence on affect based trust [5]. Trust is not the element that is supplanted by digital transformation as studies have proven [6]. They have surveyed 291 senior managers in the UK and US and in this case, digital tools can only lead to supply chain resilience by being utilized in conjunction with governance mechanisms (including trust). Trust and technology go together and not side-by-side.

Research has explained the CARE model that is used by Philips (Collect, Assess, React, Enhance). It applies machine learning predicting the sustainability level of suppliers in the future and providing actions to be taken proactively towards improvement [8]. Philips also claimed a 24% increase compared to 2019 of the suppliers registered in 2020. The outcome of that illustrates the effectiveness of a well-designed analytics-based assessment on large scales.

This framework, called DSTS, consolidates these contributions in to one scoring framework.

III. DSTS FRAMEWORK

The scoring module comprises four modules in the framework, which are Operational Performance (OP), Geopolitical Exposure (GE), Sustainability Compliance (SC) and Digital Maturity (DM). A normalized sub-score obtained in each of the modules will be on a 0-100 scale. The last DSTS is a linear combination (with weights).

A. Mathematical Formulation

Supplier i has a composite DSTS which can be defined in Equation (1):

$$\mathrm{DSTS}_i = w_1 \cdot \mathrm{OP}_i + w_2 \cdot \mathrm{GE}_i + w_3 \cdot \mathrm{SC}_i + w_4 \cdot \mathrm{DM}_i$$

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Assuming that $w_1 + w_2 + w_3 + w_4 = 1$, and each weight indicates the purchasing situation of the purchasing company. A company that has a high geopolitical exposure to politically unstable areas, can choose $w_2 = 0.35$ and; a company in a domestic market that is stable can choose $w_2 = 0.10$.

The Operational Performance sub score is based on data of ERP. It employs on-time delivery rate, on-quality rate, and as-promised quantity fulfillment as major characteristics [4]. The above three variables will be a weighted average as illustrated in Equation (2):

$$OP_i = \alpha_1 \cdot OT_i + \alpha_2 \cdot OQ_i + \alpha_3 \cdot QF_i$$

where OT_i = on-time delivery rate, OQ_i = on-quality rate, QF_i = quantity fulfillment rate and $\alpha_1 + \alpha_2 + \alpha_3 = 1$. The three inputs can be easily obtained out of typical SAP procurement modules. No manual entry of data to be done.

The sub score evaluates the country risk index, which is adjusted by sentiment, in the Geopolitical Exposure sub-score. Sadeek and Hanaoka found that ordered probit sentiment scores based on the media data have a predictive ability of disruption in the supply chain [7]. This signal (GE sub-score) is brought in in the Equation (3):

$$GE_i = 100 \cdot \left(1 - \frac{CR_i \cdot (1 + \lambda \cdot S_i)}{CR_{max}}\right)$$

CR_i is here the country risk index of supplier i basing its principal operating location, S_i is the normalized sentiment score (between 0 and 1 with 1 as the most negative sentiment), 0 is a sensitivity parameter that is calibrated on the risk aversion of the buying firm and CR_{max} is the maximum country risk index in the supplier portfolio. A score that is larger on GE sub-score, implies less geopolitical exposure. This direction is not by chance since the higher the safety of the supplier, the higher DSTS.

B. Module Inputs and Data Sources

Table 1 will be an overview of the input variables of each scoring module, where the data can be obtained/generated, and how often. Each and every transaction is reflected on every command of ERP. Related inputs are updated based on a pre-set schedule, usually daily in the basis of sentiment data and quarterly in the case of sustainability certifications.

Table 1. Module Inputs and Frequency

Module	Input Variable	Update Frequency
Operational Performance (OP)	On-time delivery rate	Per transaction
Operational Performance (OP)	On-quality rate	Per batch/shipment
Operational Performance (OP)	Quantity fulfillment rate	Per transaction
Geopolitical Exposure (GE)	Country risk index	Quarterly
Geopolitical Exposure (GE)	Media sentiment score	Daily
Sustainability Compliance (SC)	ISO certification status	Annual
Sustainability Compliance (SC)	Audit score	Annual / biannual
Sustainability Compliance (SC)	ESG self-assessment	Semi-annual
Digital Maturity (DM)	EDI adoption rate	Per transaction
Digital Maturity (DM)	API connectivity	Annual

Digital Maturity (DM)	Digital innovation index	Annual

Source: Framework based on [1][4][7][8][9]

Sustainability module is based on logic of frameworks of CARE. Instead of relying on audits to provide support on violations, the SC sub-score involves predictive indicators to show how the sustainability performance is likely to occur in the future including; the size of a supplier, sector, the geographic location and past audit history [8]. It is the same method which Philips used on a large scale.

The fourth module is digital maturity, which indicates a discovery that the digital supplier competence namely responsiveness, resilience, sustainability and digital innovation is the most important factor to be included in the digital selection of supplier in digital supply chain [9].

IV. SCORING AND RISK

The DSTS does not merely give an output in the form of a number. Table 2 presents the risk classification tiers and review intervals. It is based on the risk-sorting logic that is designed to be used to observe risks continuously instead of once selected [3].

Table 2. Risk Classification Tiers

DSTS Range	Risk Tier	Classification	Review Interval
85 – 100	Tier 1	Strategic Partner	Annual
70 – 84	Tier 2	Preferred Supplier	Semi-annual
55 – 69	Tier 3	Conditional Supplier	Quarterly
40 – 54	Tier 4	Restricted Supplier	Monthly
Below 40	Tier 5	Critical Risk	Weekly

Source: Management actions adapted from [3][8]

The standards adopted in Table 2 are not stipulated. Groups in extremely dynamic industries like mineral raw materials, semiconductors, pharmaceutical ingredients ought to reduce the levels downwards with a score of 70 being conditional and not a preference. Research revealed that only when the model parameters are set to specifics of each market, big data analytics systems can identify shortages in supplying raw materials in the initial stages [13]. The same applies to DSTS calibration. The model is a design that is context sensitive.

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V. SYSTEM ARCHITECTURE

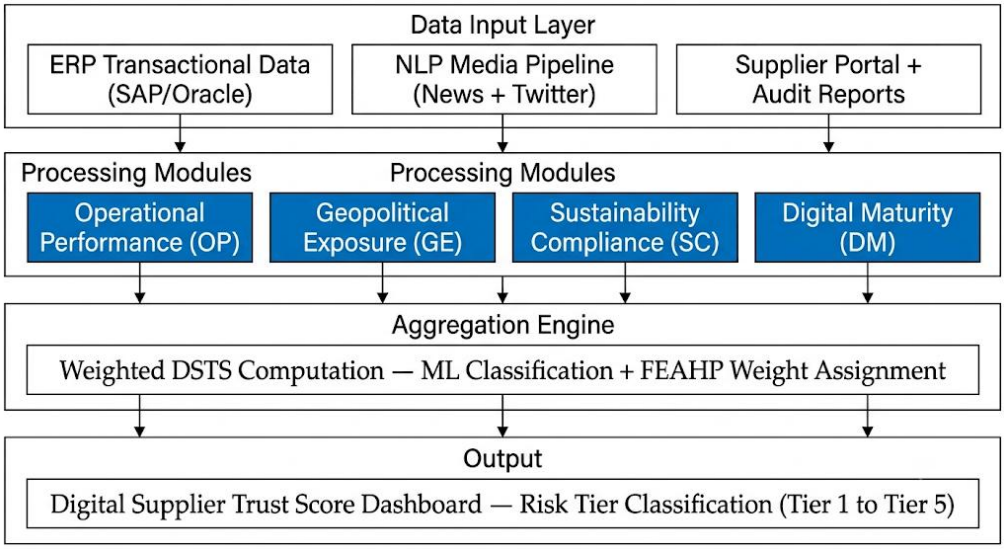

Figure 1. System architecture diagram

The four modules can be seen as part of a deployable system as shown in Figure 1. ERP layer (data extraction) directly puts into the transactional based OP module. When properly calculated, both of the methods achieve similar results. FEAHP method is more interpretable whereas SVM is capable of a better prediction technique on extensive transaction records [2].

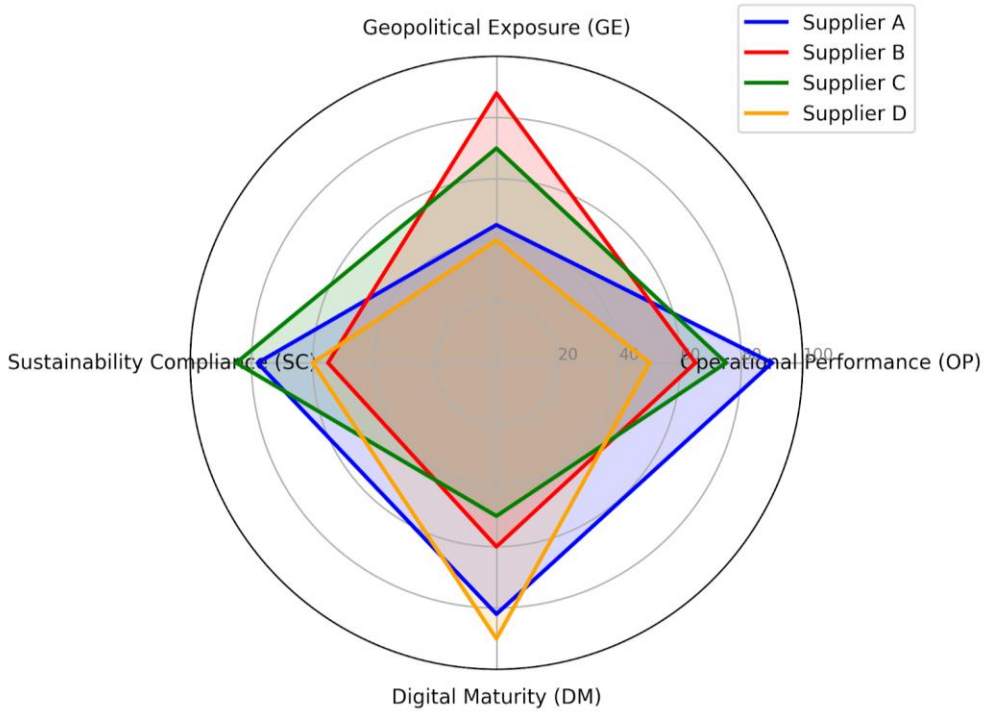

Figure 2. Comparison of suppliers across all four DSTS modules

In Figure 2, the score on individual modules is visualised into forming a supplier profile. The skewed radar polygon represents a supplier that has high OP, but a low GE but is located in a

geopolitically unstable area. It does not only indicate to procurement managers the overall level of badness of a score, but where appears to be the concentration of the risk. It was noted that sourcing decisions that align with the understanding of supplier risk can be achieved by quantifying the supplier risks into monetary values [11].

VI. BLOCKCHAIN INTEGRATION

The DSTS framework will be best applied in situations where suppliers have control to determine the integrity of the data to input in their scores. The scores that cannot be verified generate an incentive towards gaming. A supplier who is aware of its data of on time shipment is an output of the buyer has his/her ERP system and he/she cannot control the input. Nonetheless, all self-assessment of sustainability, surveys on digital maturity and proxies of sentiment are vulnerable to manipulation or even misinterpreting.

Incorporation of blockchain resorts to this. Cognition-based and institution-based are supported by DSTS framework. It renders the competence assessment rigorous and computable cognition-based trust, and audits a record of scoring entries, which cannot be tampered with. An affect-based trust is not a part of the framework. It is not a part of quantitative model. That is fine. The thing is not to computerize all the aspects of supplier relationship. The idea is to eliminate any uncertainty in the dimensions that can be computed and direct the human attention and relationship energy of the procurement managers to the mentioned dimensions which cannot be computed. It was this division of labor which was verified by studies. There is a complement between digital transformation and trust [6]. The DSTS model is considering such an empirical finding.

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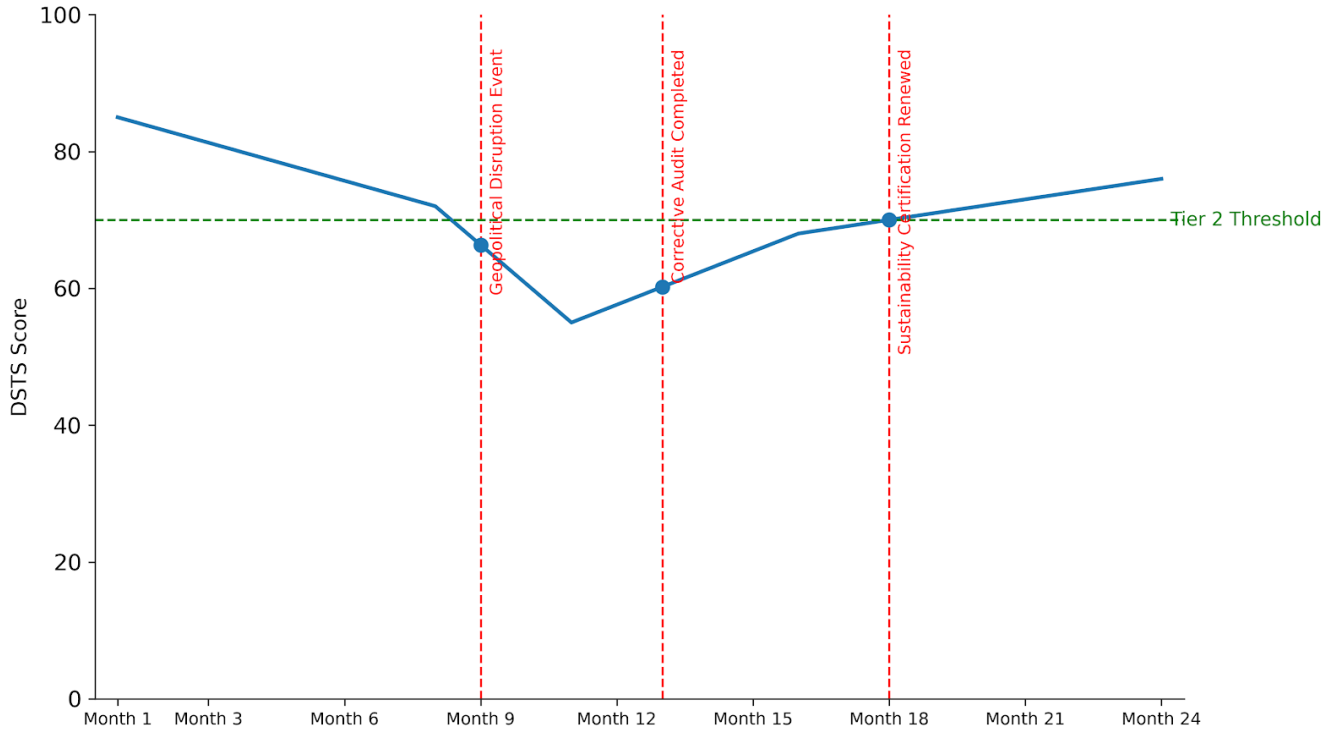

Figure 3. Timeline diagram of DSTS scores

Figure 3 shows dynamics of the scores over a time. This is one of the key contributions of this framework due to this temporal aspect. A supplier of a current DSTS of 72 and has a trend of 85 to 72 in the past six months is a risk proposition different as compared to one that has a trend of 60 to 72. The score matters. It is the course which counts.

VII. GEOPOLITICAL VOLATILITY

Geopolitical risk is a variable procurement that is first-order. Research involved a nation-wide, firm-level, production network and discovered that only 0.035% of all companies produces 23% of the country's economic exposure to production in the event of a company default [12]. The key finding of their critical review was that the firm size was found not to be predictive of systemic risk, rather network position was. Any small supplier who is on a critical node of a production network poses systemic risk as opposed to a large supplier who is on the outer of the network. Network position however, rather than country-of-origin risk, needs to be taken into consideration in the DSTS GE module.

The majority of procurement departments cannot access the supply chain of its suppliers that turn out to be the Tier 2 and Tier 3 suppliers. Surveys indicated that big data analytics of 12 mineral raw material markets across 14 risk categories could anticipate supply shortages, but also identified that markets have idiosyncratic characteristics like modes of transport, market concentration, profile by country of origin. It needs to have supervised model setup unlike its generic usage [13].

This has a practical implication to DSTS in that the single country risk index cannot be used by the GE module. It must have a customizable, commodity and sector-based risk profile which is indicative of the real supply chain topology. This is achievable. It needs to be interwoven with the databases of country risks in commerce and the networks of statistics of production at the level of the network [12].

VIII. LIMITATIONS AND FUTURE WORK

Sentiment scoring element is reliant on the quality and coverage of data of news and social media. Researchers reported that the performance of supervised models of NLP is better than unsupervised in detecting risk in domains of particular interest, whereas labels during training, which are not available in most procurement teams, are necessary in supervised models [7]. This forms an obstacle to implementation.

The sustainability module partially is based on self-assessment of suppliers. Research has solved this issue by training predictive models on overall characteristics of suppliers as opposed to using self-reported data, however, self-reporting bias still plays out in an environment where it is hard or costly to check information [8].

The weights of the module used in Equation (1) need to be determined by experts. An alternative based on data, which is less dependent on expert opinions, is Shannon entropy weighting [10]. Possible future advances of the DSTS framework is to use historical outcome data to automatedly optimize weights.

In the future, the DSTS needs to be proven on actual suppliers' databases of suppliers in a variety of industries. The case study replicating Kohli SAP-based architecture of the entire four module scoring architecture [4] is evidently the next step [4].

IX. CONCLUSION

Procuring risk is not a visible risk. It exists in the shadows since it cannot be taken into consideration by existing tools due to aggregating the appropriate signals the appropriate way. Most of the transactional data required to do dynamic Supplier scoring will be contained in the ERP systems. The risk signals can be obtained using natural language processing tools before the risks have caused any measurably harmful impact. The methods of multi-criteria decision analysis give strict guidelines on how to integrate any kind of inputs in order to get a single interpretable score. These capabilities are linked in Digital Supplier Trust Score framework. It converts geopolitical turmoil, environmental shift adherence, computer adequacy, and performance into one actionable process.

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