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Final Project Report

Achieving Resilience Through Proactive Supply Chain Risk Management	
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Project Team Lead	Supply Dynamics
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MxD Funding Value	N/A
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I. EXECUTIVE SUMMARY

Supply Dynamics partnered with The Intelligence Factory and Sympatic, a team of world-class supply chain, machine learning, artificial intelligence, and data privacy subject-matter experts, to develop a supply chain risk management (SCRM) solution and pilot the program with Rolls-Royce, a large, multi-national aerospace original equipment manufacturing company, and an MxD member company.

Problem Statement (Why the work was done):

1. As a Supply Chain/Sourcing Manager, it is difficult to obtain visibility into layers of the supply chain below the tier 1 supplier, inclusive of raw material sources.
2. It is not enough to understand event risks, I want to map them to suppliers, parts and raw materials so that I can anticipate disruptions and mitigate them.
3. I lack actionable alerts specific to suppliers, parts and materials and the ability to understand the confidence level associated with risk scores.

How the problem was addressed:

The project team developed a simple, modular, and easily-integrated machine learning module to synthesize over 60 types of risk associated with the parts, assemblies, materials, events (natural and man-made), and other metrics. The solution provides timely alerts and actionable sourcing recommendations linked to specific suppliers, parts and materials. It was piloted in a live, operational context with the goal of zero arrears for machined parts containing castings or forgings.

The project focused on the development of the risk module, referred to as the Dynamic Risk Mitigation Engine (DRME), as well as the user interface(UI) in the form of a dashboard integrated into an existing item-level visibility platform, SDX.

Project Outcomes:

Four products were ultimately produced from the project:

1. A **Dashboard** to display the risks associated with parts and materials of an OEM, and allow the user to take immediate action.
2. A **Dynamic Risk Mitigation Engine (DRME)** a modular machine learning algorithm used to generate a risk score, confidence level, and recommendation.
3. An expert-model, **Customer-Configured Risk Calculator** allowing the customer to change weights of input, and calculate risk while DRME is learning.
4. An **Altman-Z calculator** using VirtualVault technology.

Recommendations:

1. Improved Stake Holder Alignment - Expectations from all parties need to be over-communicated up-front and agreed upon at the highest levels of an organization.
2. Understand Customer-Vendor Dynamics - Many of the risk factors required participation and data sharing from Tier 1 and Tier 2 suppliers and tenuous relationships prevented these specific factors from being included in the risk model.
3. Data Access Cleared and/or Understood Prior to Starting – Because several of the risk factors related to the parts and materials specifically, much of the data could not be shared as discrete values.

4. Manage and Communicate Changing Requirements and Scope – The team should over-communicate on all changes and obtain the buy-in of the team before proceeding with any major extensions and changes.
5. Consider FedRamp-approved environment for future deployments - Given the restrictions and export control requirements for much of the data/parts, it is highly recommended that future solutions/projects be launched within a FedRamp approved environment.

II. PROJECT DELIVERABLES

The following list includes all deliverables created through this project. With the exception of the Pilot Deployment, these deliverables should be accessible on the MxD membership portal in accordance with the rights defined by the Membership Agreement. Specific deliverable types include, but are not limited to, the following items:

Table 1: 20-05-01 Project Deliverables

#	DELIVERABLE NAME	DESCRIPTION	FORMAT OF DELIVERY
1	DRME	Modularized, ML predictive analytics decision engine	JSON code, zip folder with .exe
2	Pilot Deployment	Solution deployment in Rolls-Royce operational environment	System deployment/ documentation
3	DRME User Guides/Training	Work Instructions and training deck	PDF report
4	How to Get Started Guide	Templates needed for implementation; JSON code formatting for inputs/outputs of DRME setup	PDF report
5	Report on Tech Recommendations	Reports on technology gaps, and recommendations for future enhancements	PDF
6	Technical Documentation and/or White Paper for DRME	The Intelligence Factory – Technical Doc for DRME	PDF/Whitepaper
7	Anonymized Data Sets	Anonymized Research datasets- for training supply chain ML / models	Flat file
8	Case Study(ies)	Summary of outcome of Pilot deployment to be used for future projects	PDF report
9	Recommendations	Provide recommendations for future technology development/ enhancement, overcoming	PDF report
10	Incremental Test Plan	Summary of testing and issues found and addressed	PDF report

III. PROJECT REVIEW

The purpose of the project was to develop a simple, modular, and easily integrated machine learning module that will synthesize over 60 types of risk associated with…

- Assemblies
- Parts
- Materials

- Events (man-made and natural disasters)
- Historical performance
- Line of balance variances and other metrics

….and provide timely alerts and actionable sourcing recommendations linked to specific suppliers, parts and materials. Once developed, the solution was to be piloted in a live operational context with the goal of zero arrears for machined parts containing castings or forgings.

The goal of the solution was to help an OEM's users answer the question: "***Will the next shipment be on time?***" There are *numerous* inputs to this question for a large multi-tier OEM; the DRME and the dashboard used to display the results were trying to help the users a) answer this question, and b) take action if the shipment was not going to be on-time.

Buyers and commodity managers today are typically consumed with the tactical, fire-fighting aspect of their daily duties: managing those parts that are most in danger of shutting down a line, or chasing parts that are the latest due to dock. They use a combination of spreadsheets, existing metrics, and past performance indicators to attempt to manage their parts/supply chain. There are 3rd party risk-event notification systems but they are based on entity/site-level risk and do not include part data nor OEM forecast and/or delivery data. For this reason, it is difficult to take the higher-level strategic view and synthesize all the inputs together.

Use Cases & Problem Statement

"As a Supply Chain/Sourcing Manager, it is difficult to obtain visibility into layers of the supply chain below the tier 1 supplier, inclusive of raw material sources.

It is not enough to understand event risks, I want to map them to suppliers, parts, and raw materials so that I can anticipate disruptions and mitigate them.

I lack actionable alerts specific to suppliers, parts and materials and the ability to understand the confidence level associated with risk scores."

Specific, Primary User Case:

*As a **Rolls Royce Supply Chain/Sourcing Manager**, I want to achieve zero arrears for any part number manufactured from castings and forgings. I also want to anticipate disruptions in my supply chain before they happen.*

Scope & Objectives

To help a supply-chain professional understand the risks associated with their supply chain, the scope of the project included:

1) Mapping an actual multi-tier supply chain at a leading Aerospace & Defense OEM. This included loading all parts and material for 6 target Tier-1 vendors into an existing aggregation platform, SDX, and obtaining the forecast for these parts/material on a regular cadence.
2) Develop a modular, ML enabled risk mitigation engine that can be integrated into any manufacturer's standards-based data store to calculate risk and provide mitigation recommendations.
3) Minimize false positives (alerts that are meaningless).
4) Pilot the solution in a real operational context and measure results to baseline OTD performance.
5) Publish findings and best practices.

Planned Benefits

The solution was to provide the following advantages to the user:

1. Ability to synthesize 60+ different risk factors, calculate supply chain risk and attach those risks not just to suppliers, but to impacted parts and materials.
2. Enhanced on-time delivery.
3. An ML model that trains itself over time to more accurately characterize risk and those mitigation activities that are most effective in mitigating it.
4. Actionable alerts that identify impacted suppliers, parts, and materials.

IV. TECHNICAL APPROACH

The project involved technical development for all four of the products listed which centered around the need to have a risk score, a recommendation (ignore, monitor, expedite), and a confidence level for the accompanying score/recommendation for each part-vendor pair. The assumption was that all vendor-part pairs would begin with a risk score of 60 on a scale of 0-100, a recommendation of Monitor, and a confidence of 50%. Inputs to the system included: risk factors (see Appendix E), on-time delivery reports, and the action(s) taken by the user to either mitigate or close vendor-part pairs. The output of the system for each vendor-part pair included: 1) the risk score, 2) a recommendation and 3) the confidence.

The Dynamic Risk Mitigation Engine leveraged four key technologies:

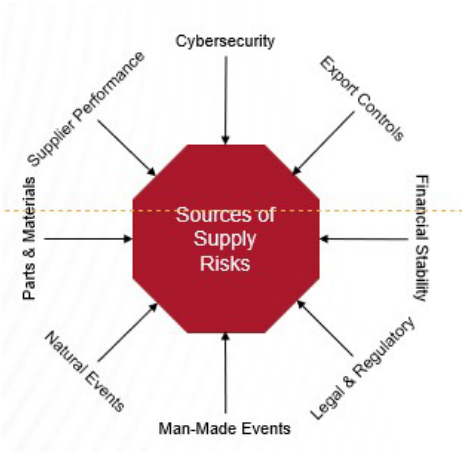
1) Weight of Evidence Reasoning
2) Ensemble Learning
3) Adaptation Over Time
4) Virtual Vault

Weight of Evidence Reasoning

Dozens of Risk Factors affect a given supply chain at any point of time. Because some risks have larger impact(s) than others, OEMs can have input on weight of individual risk factors. The more risk factors that are “true” at any given point, the more evidence of a likely disruption.

There are several different ways to disrupt a supply chain; and for this project, they were grouped into 8 categories:

1. Cybersecurity
2. Export Controls
3. Financial Stability
4. Legal and Regulatory
5. Man-Made Events
6. Natural Events
7. Parts and Materials
8. Supplier Performance



These are an initial set; the DRME also allows for Customer-specific risk factors unique to each company's business model and operational considerations.

Within each category listed, there can be anywhere from 2-20 individual risk factors (see APPENDIX E Risk Factors for complete list). For purposes of explaining Weight of Evidence Reasoning, Man-Made events will be highlighted.

Man-Made Events

Risk Factor	Impact Weight (1=low, 5=high)	Force to MONITOR? (1=yes)	Force to ACTION? (1=yes)
Bankruptcy	5		1
Factory Disruption	5		
Factory Fire	5		
FDA/EMA/OSHA Action	5		
Force Majeure	5		1
Mine Shutdown	5		
Recall	5	1	
Business Sale	4	1	
Business Spin-off	4	1	
Company Split	4	1	
Corporate Restructuring	4		
Merger & Acquisition	4	1	
Port Disruption	4		
Profit Warning	4	1	
Protest/Riot	4		
Regulatory Change	4		
Chemical Spill	3		
Fine	3		
Geopolitical	3		
Labor Disruption	3		
Labor Violation	3		
Leadership Transition	3		
Legal Action	3	1	
Price Fluctuation	3		
Airport Disruption	2		

Within **Man-made Events** we pick up several factors from a third-party source (i.e. Exiger, Resilinc, Interos, etc.) Each factor is assigned a **weight** based on how seriously it can impact receiving the next shipment on time. Some are likely to be very impactful – like bankruptcy, a factory fire or a mine shutdown – and receive a score of 5. Some are less impactful – like a chemical spill, a legal action, or an airport disruption and these receive lower scores, in some cases down to 1.
The more of these factors that are true right now, the more evidence we have that a disruption is likely – this is what is meant by **weight of evidence**.

In addition to the weights, some events are so important that there is a need to immediately set off an alarm, so the DRME allows for **Force to Action** alerts in addition to weight of evidence.

Action flags may be unique to each business, so they can be customized when the DRME is installed. *If ANY of the flagged conditions arise – regardless of the weight of evidence – the alert will get the user's attention by forcing either MONITOR or EXPEDITE.*

This weight of evidence occurs for each of the risk categories. The following risk factors will trigger **Force to Monitor:**

- Financial Stability
- Merger & Acquisition
- REACH/RoHS
- Profit Warning
- Company Split
- Legal Action

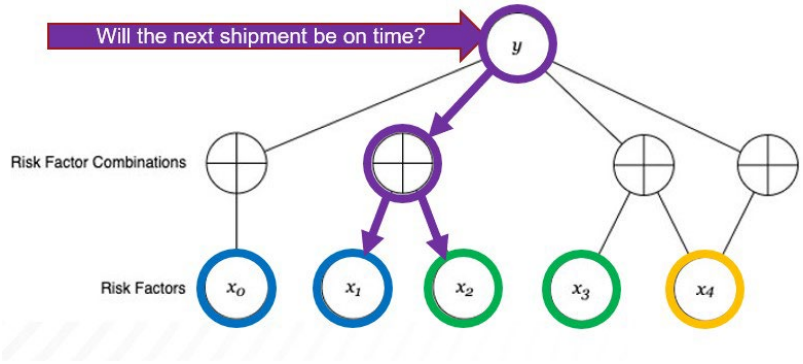
- Recall
- Power Outage
- Forest Fire
- Production Readiness
- Business Sale
- Tornado
- Hurricane/Typhoon
- Vendor Quality Rating
- Business Spin-off
- Extreme Weather
- Flood

The following risk factors will trigger **Force to Expedite:**

- Cyber attack in progress
- Bankruptcy
- Earthquake > 4.0
- Life Cycle Stage = Obsolete Part
- Force Majeure
- Volcano

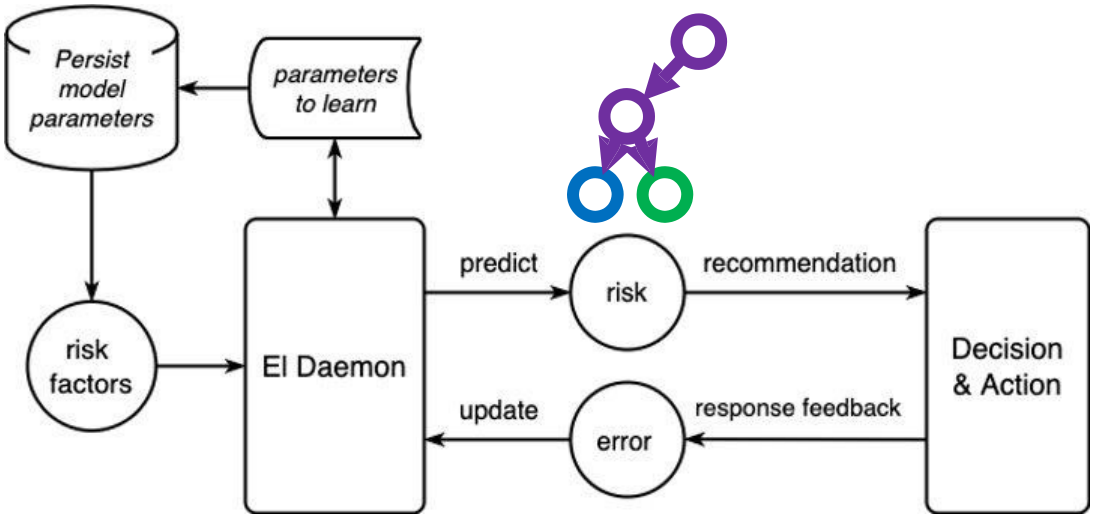
Ensemble Learning

Ensemble Learning is machine learning that combines weight of evidence, a Markov network, and user feedback to predict the combination of risk factors which are most impactful.



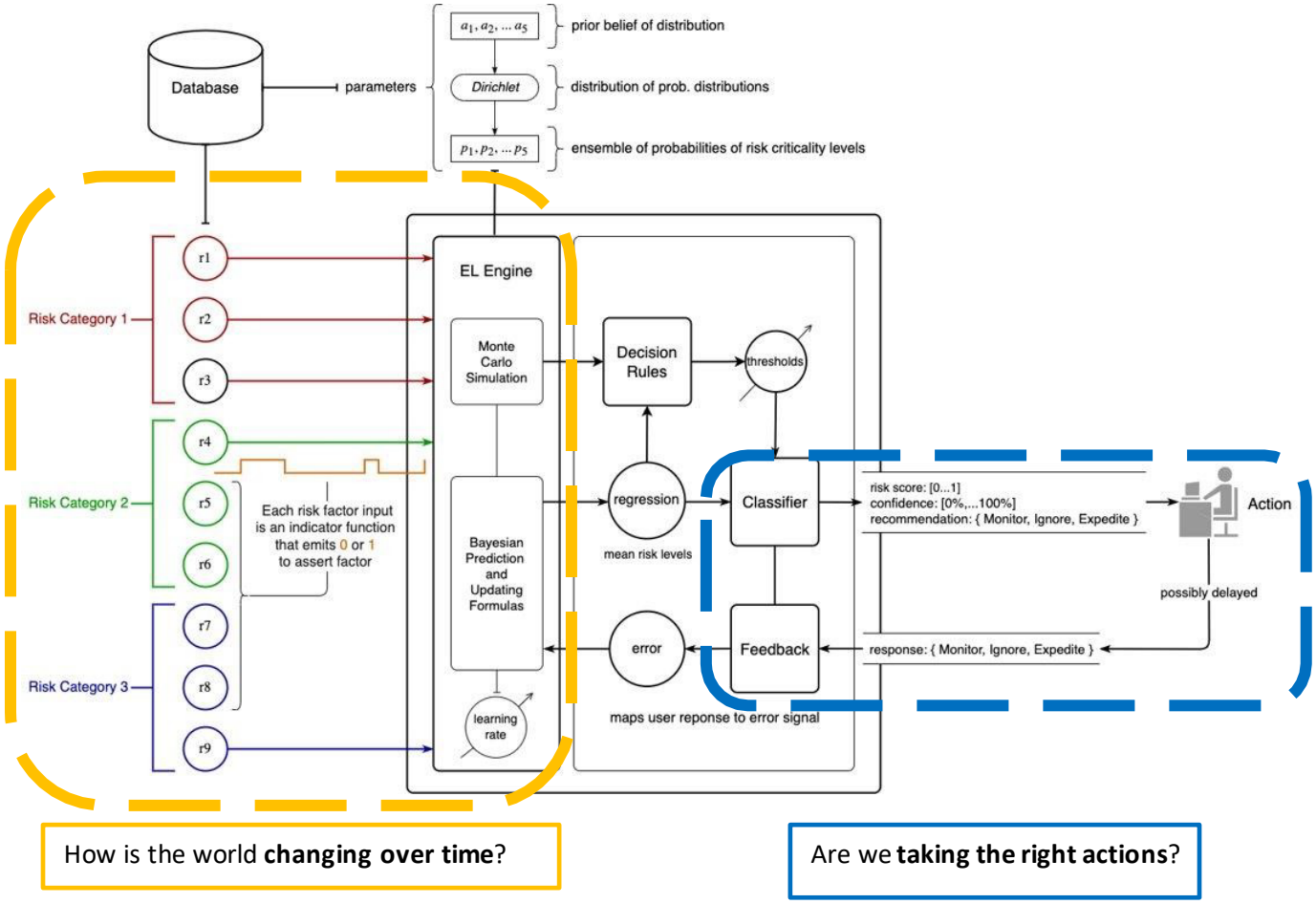
In the DRME, risk factors can come from any category, so it looks for combinations of variables that together make good predictions. The variables may come from the same category or from different categories.

This process is then locked in a loop so that as new data appears, the model considers what combinations make the best predictors while observing and tracking the users' actions in response to events.



Adaptation Over Time

The DRME continues to update the weight of evidence, so it concentrates on the right factors at the right times. The tool measures & records actions taken to ensure improved results next time. This technology also includes dynamically updating the risk scale and recommendations based on prior performance.



Virtual Vault

Sympatics' VirtualVault technology is a cloud-based, dev-ops automation allowing "content sharing" without revealing sensitive raw data. For this project, the technology was used to share supplier financial metrics and calculate an Altman-Z score providing a measure of financial stability.

If the suppliers are public companies, their finances are disclosed, but this is not true for private parts shops that are a large part of the market. The Altman-Z score is a calculation to determine whether a company, especially manufacturing companies, is in financial peril and at risk for bankruptcy. It takes into account profitability, leverage, liquidity, solvency and activity ratios without revealing any of the specific values.

For this project, a vendor would receive notification to initiate the vault. If the invitation is accepted, the vault would spin-up automatically in a secure environment and the supplier would enter their

financial data and the Altman-Z score would be calculated and published. The vault runs, publishes the output and then the environment self-destructs leaving no copy of the data once it is complete. The supplier then *chooses* whether to share the Altman-Z score with their customer or not; regardless of whether it is shared, the vault and initial data are completely destroyed; all that remains is the Altman-Z score.

V. RESULTS

Overall, the project was a success and demonstrated the art of the possible for creating a tool to synthesize part and entity risk and provide the user with actionable choices in dealing with the associated risks. Leveraging past vendor performance(s), incorporating current on-time delivery reports and including 3rd party risk event data successfully provided users with early warning of potential supply chain disruptions. That said, the project was not ultimately successful in helping to achieve zero arrears for parts made from castings and forgings, and only minimally improved the On Time Delivery (OTD) performance across the target vendors from the beginning of the project 2021, to Q1 2023. Lastly, while the risk solution did leverage the customer's actual delivery reports, the customer did not actively use the line of balance reporting capability within the user interface.

▪ Zero arrears for parts made from castings and forgings	
▪ Measurement method for On-Time Delivery of parts at Rolls Royce in arrears (line of balance capability in SDX)	
▪ Early warning of potential supply disruptions	
▪ Dynamically curated event supplier part and material risks (associate risks and combine in one place)	

System Overview

The final project was the integration of three systems:

1. The machine-learning based Dynamic Risk Mitigation Engine (DRME)
2. The expert-model Customer-Configured Risk Calculator
3. The dashboard user-interface which displays the risk score, recommendation, and confidence results from #1 and #2 and allow the user to mitigate and close risks.

There was only one technology deliverable: the DRME source code which was delivered to MxD as an executable file.

Table 2: 20-05-01 Technology Deliverables

#	DELIVERABLE NAME	DESCRIPTION	FORMAT OF DELIVERY
1	DRME	Modularized, ML predictive analytics decision engine	JSON code, zip folder with .exe

System Requirements

The system requirements resulted from input from all project partners including the pilot partner, Rolls-Royce. As the project sponsor, Supply Dynamics led the design and output requirements based on the statement of work and desire to have the solution simple and actionable. Rolls Royce

provided feedback for the risk categories and risk factors, as well as the customer-based risk factors which were included. The Intelligence Factory provided the requirements and ultimate design of the DRME, as well as the lambda function which was used to communicate with SDX and the dashboard. Blue Roof Labs and Supply Dynamics provided the requirements and design of the customer-configured algorithm which works in tandem with the DRME while the machine-learning is being trained. Sympatic provided the requirements and design of the VirtualVault for the Altman-Z score calculation.

A user of the system would likely require support from their IT professional to integrate the DRME source code into a program and/or solution within their company that can leverage the required inputs. At a minimum, the input required includes:

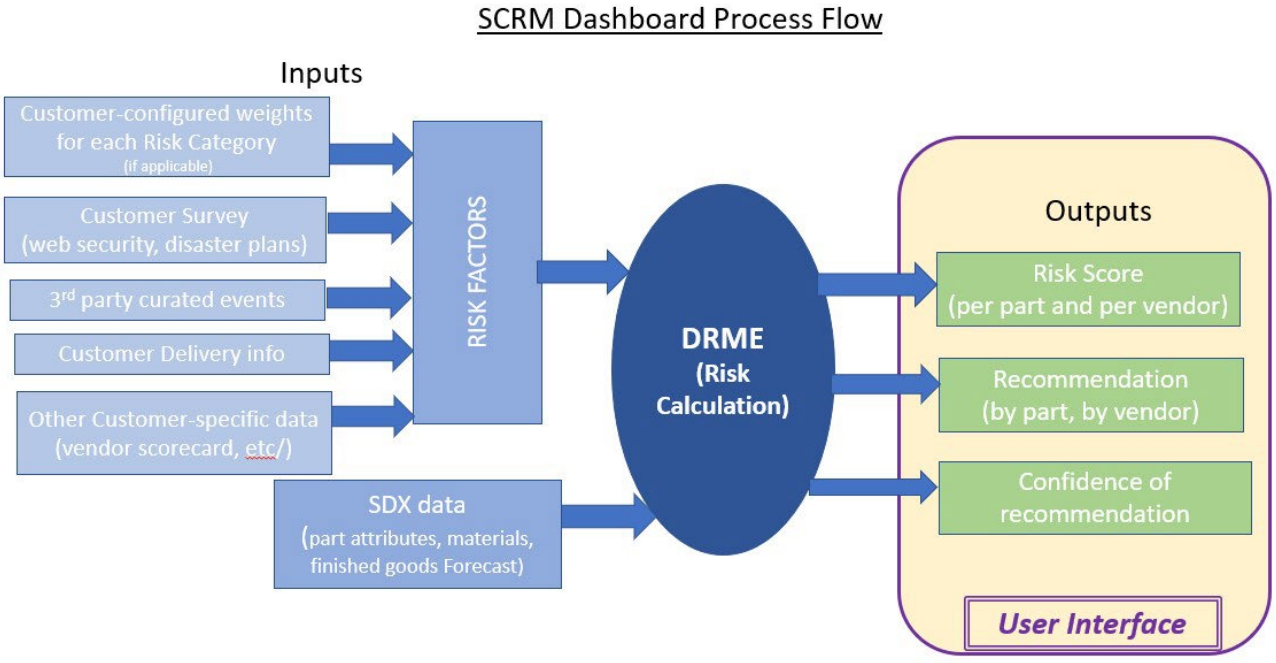
- Vendor id, part id_RISK FACTOR

The **Vendor ID** is either an id from the system where it will be applied and/or could be an OEM vendor code. It must be a unique identifier for the vendor in question.

The **Part ID** is either an id from the system where it will be applied and/or could be the OEM part number. It must be a unique identifier for the part in question.

The **RISK FACTOR** is one of the 60+ risk factors identified to be active and therefore applied to the vendor id-part id pair listed.

System Architecture



The system architecture is relatively simple at a high-level: the inputs are the application of various risk factors as a vendor-part pair. We selected over 60 risk factors to use as inputs: external and man-made events from a 3rd party source, along with specific part and material attributes, sourcing structures (sole vs. dual), on-time delivery and vendor score card metrics. These are used as

inputs to the DRME and the risk either applies or does not apply based on the customer's weight of the category in question and their risk threshold. The inputs are typically in JSON format as outlined in the documents **How To Get Started: Using the DRME Functions,** and the final technical document, El Daemon – Technical Paper. The output of the DRME is the Risk Score, Recommendation, and Confidence of that score and recommendation. The output as well as the users' action/mitigation can all be hosted within a created User Interface. The UI could be in the form of a dashboard or a windows-based system depending on the use case.

Target Users & Modes of Operation

Target users are those supply chain professionals at any OEM who are responsible for ensuring the parts and materials they are responsible for arrive at the dock ON TIME. This includes buyers, commodity managers, planners looking at specific vendors and parts as well as supply chain managers attempting to assess the risk of the overall supply chain.

If the DRME results are being displayed in the dashboard user interface, the various filters and search features allow users to look at all vendors/parts or just those they are responsible for. Regardless of whether the user is assessing the risk using the Ensemble Learning model or the Customer configured model, all mitigations and event closures are recorded by the machine learning and used to update predictions, confidences levels, and risk scores.

Software Development/Design Documentation

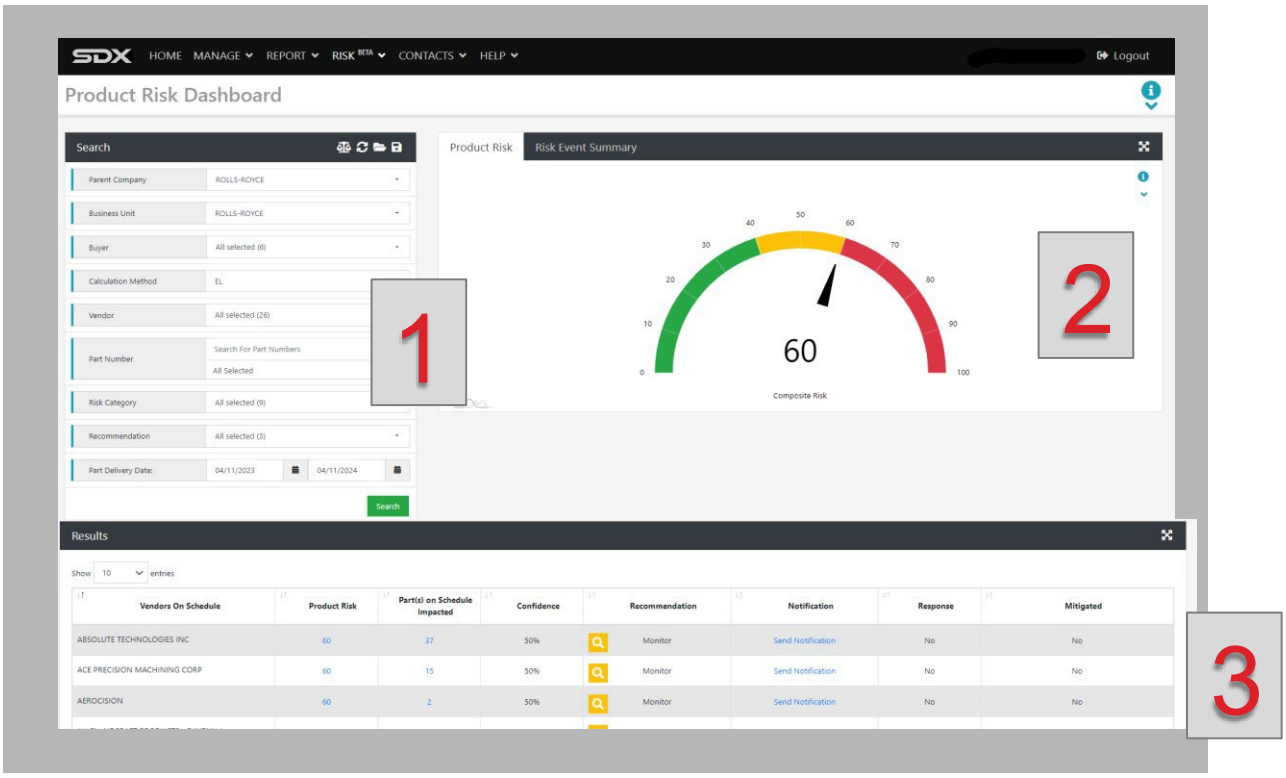
As stated, the DRME was designed by The Intelligence Factory with the user interface designed by Supply Dynamics and hosted in the existing SDX platform. Specific formatting for data inputs as well as format of data output can be found in the **How To Get Started Guide**. Depending on the size of the supply chain, it is suggested that a User Interface be leveraged for easier consumption of the output as well as to allow the mitigating action to be taken.

User Interface – Dashboard Design

Although this is not a documented deliverable of the project, the user interface was developed in conjunction with the DRME to allow for quick user analysis as well as the ability to take action directly from the dashboard.

The Dashboard included three specific areas to enhance the user experience (see image below)

1) The Search Panel – allowed the user to filter the display/results by:
   - Business Unit
   - Buyer/Commodity Manager
   - Vendor
   - Part Number
   - Risk Category
   - Recommendation
   - Date Range
2) Composite Risk and Risk Event Summary: Displays the overall composite risk for the population of parts selected in the Search Panel. The event summary allows users to click into each category and see a description of those risk factors affecting specific suppliers.
3) Results Table: Shows a breakdown of the impact summary by supplier and the parts. The Confidence score reveals the completeness of the data based on prior input and freshness of data. The table shows the parts impacted and reveals parent/child relationships if they exist, the machine learning recommendation of Ignore, Monitor, or Expedite helps users focus on what matters. The results table also includes the Mitigation feature allowing users to record what if any action they have taken on these results. They can also send an email to the supplier directly from the dashboard inquiring about the potential risk mentioned and the supplier's response is registered automatically. Finally, a status button allows users to close those parts and/or risks they have already addressed and are no longer of interest.



VI. DISCUSSION & ANALYSIS

The Covid-19 pandemic brought the spotlight to the many risks of large, multi-tier supply chains. While there are several 3rd party solutions which can provide curated risk data at the event or entity level, the DRME takes this risk down to the component and material level and allows an OEM to quantify the impact an event or supplier might have on the overall forecast. Because we have integrated part and material information along with historical supplier performance data, the OEM has a much deeper look into the risks of their supply chain. In addition, machine learning can continue to refine its algorithm over time and understand which risk factors truly help predict whether a shipment of part(s) might be late the next time.

Industry Impact

This type of technology has the most impact for large, multi-tier Original Equipment Manufacturers who typically are not making the majority of their parts, but rather rely on a large network of suppliers, and their suppliers' suppliers to deliver parts and subassemblies which will ultimately be part of the final product. A machine-learning enabled risk model has the potential to alert supply chain experts when a part and/or assembly is at risk of being delivered late – and the model works as well for those parts/products with very long lead times such as castings and forgings, as well as just in time and/or Commercial off-the-shelf (COTS) components.

As with any data-driven system, the performance and output of the solution is only as good as the data that feeds it. In other words, "garbage in = garbage out." While the number of risk factors is customizable, there should be a combination of external risks (natural and man-made event risk) as well as internal factors (raw material availability, sourcing, number of validated or mapped Tiers,

supplier quality, etc.). All of this data needs to be consumed by the DRME in an organized manner and the output needs to be in a usable format – all of which requires time and effort by the OEM.

Because it is designed for OEMs, the DRME is useful for those OEMs supplying the government, not necessarily for the government to use itself.

Key Performance Indicators & Metrics

While there were slight improvements in the On-Time-Delivery for targeted vendors and parts (see Table 4), the overall goal of achieving zero arrears for targeted machined parts with castings and forgings was not ultimately achieved.

To quote from Rolls Royce as the pilot user:
"Overall, the project was a success and demonstrated adequate capability against the problem statement. The DRME provides useful insights to which risk factors are more indicative of on-time delivery, it does not give a high number of false positives, and it is easy to use. The DRME could have benefitted from a longer trial period to further refine its thresholding for when it escalates recommendations (ignore, monitory expedite)."

Table 3: KPI Metrics

KPI/Metric	2021 - Baseline	Q1 2023 (Results)	Project Goal
OTD Performance Overall (On-Time Delivery)	53%	--	95%
Aggregate OTD for targeted parts	44%	**72%**	95%
OTD - Vendor A	41%	**45%**	95%
OTD - Vendor B	56%	**64%**	95%
OTD - Vendor C	71%	**81%**	95%
OTD - Vendor D	44%	**44%**	95%

Accessing the Technology

The DRME source code will be made available to MxD members and specific formatting of inputs and outputs can be found in the How To Get Started documents: How to Get Started: DRME Setup, and How To Get Started: Using the DRME Functions. There is no IP needed to use the technology. However, there is likely a need for a Lambda wrapper if the source code needs to interact with other code and/or if the output will be displayed in a specific user interface. For purposes of this project, the output was displayed in a dashboard within the SDX solution, but could be displayed within a database, spreadsheet, graph, etc.

Familiarity with Python code and the integration of the code into existing platforms is required for the solution to be fully useful. It

Data Needed:

In addition to external risk factors such as weather events, man-made events, and specific risks relating to sourcing, it is suggested the following risk factors could be leveraged with the information listed in Table 5.

Table 4. Recommended Sponsor Data

Risk Category	Risk Factor	Information Needed
Supplier Performance (Customizable)	On-time delivery performance for given part (across all Vendors forecasted for given part)	OEM weekly delivery data/report
	Vendor on-time delivery by part	
	Vendor on-time delivery performance across all parts	Vendor Score Card
	Vendor quality rating	
Customer Curated (Customizable)	Parts Shortage	On Time Delivery Metric/Report
	Part Concession Frequency per Vendor	Vendor concession data (weekly or monthly)
	Vendor Concession Frequency (across all parts)	
	Vendor Escapes in last 6 months	Vendor Score Card or Escapes report
Parts & Materials	Line of Balance Variance - orders placed vs orders forecasted	Open Order/Shipment reports from Tier 2 suppliers
Cybersecurity	CMMC (Cybersecurity Maturity Model Certification) Level	Completed Survey by Vendor
	Disaster Recovery Plan in Place	
	NIST 800-171 compliance (submit to SPRS)	
	Business Continuance policies and procedures	
Export Control	Export Control Status (Policies and procedures)	
Financial Stability	Z-Score Calculation for Financial Stability	Completed Virtual Vault Z-Score Calculator by Vendor

Lessons Learned

1. **Vendor Level Risk vs. Part-Level Risk**
   The initial project requirement included a *recommendation* and *mitigation* at the **Vendor-level.** In other words, a risk score and recommendation could ONLY be viewed at the vendor level and the user would select an action based on **the vendor as a whole**.

   Once the solution and DRME was being used in the dashboard User Interface, the team realized this was not granular enough for an OEM and its users: they are looking at risks and delivery at the *PART* level. The project was paused and the entire model was updated to reflect this. The DRME now evaluates the risk – and most importantly allows for action – at the **part level**. The dashboard UI also accommodates this change. This helps to train the ensemble learning at a more granular level and provides greater value to the user in terms of understanding his/her supply chain risk. This was a significant change in scope from the initial project but we felt it was the only way to make the dashboard truly useful to the customer.

2. **Address Data Access for Controlled Unclassified Information, Proprietary Data**
   Data sharing, cyber-security and clearance issues, and handling of sensitive data across multiple project partners needs to be part of the initial agreements and addressed prior to the project beginning.

3. **Address Customer-Vendor relationship issues early**

Overall, stakeholder alignment both internal and external is crucial to the success of any strategic-focused effort. To have full visibility of a supply chain's risk profile engagement of Tier-1 vendors is a necessity. The OEM or sponsor will want to have participation in Bill of Material validation – having the supplier validation their Bills of material by stating whether they make or buy the part in question; if the raw material is sole-sourced or multi-sourced, what the lead times are for the part in question and the raw material (Tier-2) supplier and sizing. Participation in any material aggregation and/or directed-buy program should be included in program language.

4. **Dedicated resources required to implement any SCRM Effort**
   Efforts to implement and manage Supply Chain Risk Management program cannot be extracurricular, but rather requires dedicated resources to ensure stakeholder alignment and program success. Too often, SCRM becomes someone's part time job in which case the daily tasks and emergencies will always trump the strategic efforts.

5. **User Experience Simplicity Is Essential**
   The user interface for any SCRM solution needs to be simple and easy to use. Ideally, the user interface connects directly to the OEMs part and forecast data as well as any past performance records for the suppliers.

VII. CONCLUSIONS & FUTURE WORK

Overall, the DRME and the dashboard demonstrated the art of the possible and can provide a spring board to future supply chain risk management solutions. If machine learning is to be used, raw data inputs are required for optimal risk results and measurements. If the customer prefers not to use machine learning, or cannot use machine learning due to sensitive and/or controlled data, an expert-model calculation system can be used.

Next Steps & Challenges

Possible future work and next steps for improving the DRME and dashboard include:

1) Replicating the solution using multiple curated risk events/inputs. There are several sources for curated risk at the event and entity level and it would be interesting to compare the results of the DRME using different sources given their coverage and quality vary greatly.
2) Create a DRME to analyze the risks using raw input data – either with parts and/or a supply chain that did not include restricted data, or by having the algorithm run in a secure environment.
3) Launch the entire solution in a FedRamp approved environment.

Transition Plan

The table below provides a catalog of all of the project deliverables and their respective transition routes. Deliverables can transition through deployment at an industry member's site, as an educational reference or through a commercialization effort. Each of these transition routes are detailed below.

Table 5: Deliverable Deployment Summary

#	DELIVERABLE	TECHNOLOGY	EDUCATION	COMMERCIALIZE
1	DRME	X		POSSIBLE
2	Pilot Deployment	X		
3	DRME User Guides/Training		X	
4	How to Get Started Guide	X		
5	Report on Tech Recommendations		X	
6	Technical Documentation and/or White		X	
7	Anonymized Data Sets	X		
8	Case Study(ies)		X	
9	Recommendations		X	
10	Incremental Test Plan		X	

The majority of the deliverables for the project will be used to educate others on the possible solutions for Supply Chain Risk Management. The remainder of the deliverables focused on the technology integration of the DRME – the source code itself, the How To Get Started Guide and the anonymized data sets. It is possible to commercialize the DRME if the data set(s) for required inputs existed.

VIII. APPENDICES

Appendix A: Definitions

Term	Definition
DRME	Dynamic Risk Mitigation Engine
SCRM	Supply Chain Risk Management
EL	Ensemble Learning – Machine Learning employing greater than 1 technique to train an algorithm.
ML	Machine Learning
UI	User Interface – for purposes of this project the UI refers to the dashboard

Appendix C: Validation & Testing

All testing and validation was documented in the Functional Testing Log document submitted as deliverables. The log allowed a variety of users to test functionality of the software, document findings and categorically address functional issues.

In addition to the functional testing log, there were two specific experiments performed:

#1 Sparseness Testing and Results:

The goal was to answer the question: "What happens to the risk modeling system with increasing amounts of missing data?"

Having good data doesn't always mean good results. This experiment addressed two possibilities:

a. Random Data Sparseness – This is usually associated with inconsistent data collection. Any one of the 60+ risk factors could be missing at any particular time, so how many can be missing before it affects the risk score significantly? Likewise, what happens if the MONITOR or ACTION alarms fail to trip when they should?
b. Categorical Data Sparseness – This is usually associated with a data provider going offline and/or being "blind" under certain conditions. In this case, the system could lose an entire CATEGORY of data at a time. Does that have more or less of an impact than random sparseness?

Tornado Use Case

Random Data Sparseness
(0% is the REFERENCE CASE – or perfect data collection)

Risk Score - Average Results

Data Sparseness--->	Day 1	Month 1	Endgame
	1	30	360 days after event
0%	5%	23%	37%
25%	3%	23%	28%
50%	2%	12%	18%
75%	1%	6%	8%
100%	0%	0%	0%

False Negative Rate (Missed Event)

Data Sparseness--->	Day 1	Month 1	Endgame
	1	30	360 days after event
0%	0%	0%	0%
25%	9%	0%	0%
50%	25%	3%	0%
75%	63%	13%	9%
100%	100%	100%	100%

Categorical Data Sparseness
(0% is the REFERENCE CASE – or all categories are present)

Risk Score - Average Results

Data Sparseness--->	Day 1	Month 1	Endgame
	1	30	360 days after event
0%	5%	23%	37%
25%	4%	17%	26%
50%	3%	12%	18%
75%	1%	4%	9%
100%	0%	0%	0%

False Negative Rate (Missed Event)

Data Sparseness--->	Day 1	Month 1	Endgame
	0	30	360 days after event
0%	0%	0%	0%
25%	3%	3%	0%
50%	16%	6%	3%
75%	53%	38%	9%
100%	100%	100%	100%

Looking at the Use Case of one risk factor: a Tornado we see several things:

- There are two ways to set off a Monitor or Expedite alarm: one with increasing RISK SCORE and another based on TRIGGER VARIABLES. In order for the data sparseness to have a significant negative impact, it has to affect BOTH of these mechanisms SIMULTANEOUSLY.

- Random sparseness has difficulty beating the triggers. The more significant the event, the more triggers have to be defeated by having their data go missing. The more significant the event, the more triggers get tripped and the more data that would have to go missing before the system fails to notice an issue.

- Categorical data sparseness has difficulty beating the risk scoring. Losing an entire category can zero out that contribution to the top-level risk score, but the other categories are not necessarily affected since they come from different diverse data sources. By not having all the data collecting eggs in one basket, we ensure we always get some risk signaling even when multiple categories fail.

- In the end, if there are holes in enough data – at random or by category – the entire risk modeling system can be "blinded." Because it was designed it to minimize false alarms, it can

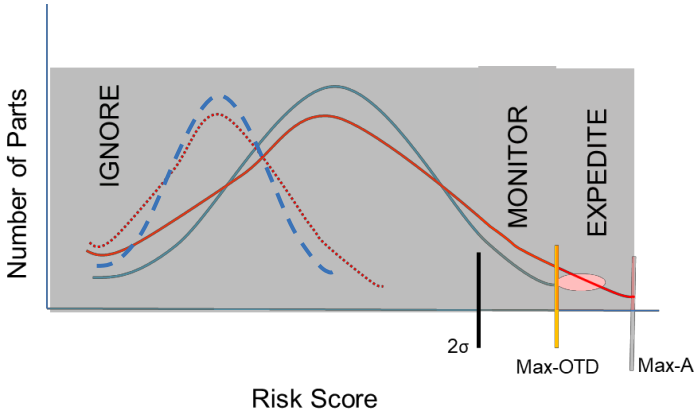
be squelched by missing data…but it takes a LOT of misses before the system performance is seriously impacted (which is GREAT!).

#2 Risk Distribution:

Once the dashboard/risk algorithm was up and running, the team was surprised to find a very limited distribution of risk scores among the parts and suppliers being targeted – they were skewed to the "low end" of the curve. For example, the max risk score we were seeing was a 35 out of 100 – and nearly all parts had a recommendation of IGNORE. In taking a deeper look, we realized this was the result of a few factors including but not limited to

- the limited number of suppliers, the fact they were all "difficult" suppliers with traditionally late parts
- the initial design requirement to minimize the number of false positives, i.e. not alerting a buyer or commodity manager to Expedite a part if it wasn't needed
- the desire to have the system "learn" and adapt over time with input from users

The team triple-checked the risk calculations and they were correct. However, we wanted to provide the user a means of focusing on the highest risk items, even though the initial scale showed them as "Ignore." Ultimately, the team came up with an elegant solution…..which lends itself to the "**adaptation over time**" initiative. The new scale is DYNAMIC – and is set using the risk scores of the PRIOR week's deliveries allowing user the user to take action on those parts most at risk for late delivery.



Methodology:

- Max-A rescales to 100
- EXPEDITE = Max-OTD to Max-A
- MONITOR = 2σ to Max –OTD
- IGNORE = less than 2σ

The risk re-scale takes the MAX risk score from ALL parts delivered the prior week - MaxA and forces this to 100. We then take the highest risk score from those parts delivered ON TIME, and make this the cut off for EXPEDITE recommendation. The cutoff for the MONITOR recommendation is the second std deviation from the average of on-time parts. Everything below this threshold becomes IGNORE. This allows the user to focus on *RELATIVE LATENESS,* and again, is updated weekly.

Appendix D: User Resources

User resources are separate documents and include the following which were submitted to MxD:

1. How to Get Started: DRME Setup
2. How To Get Started: Using the DRME Functions
3. Dashboard Work Instructions

Appendix E: RISK FACTORS

Category	Risk Factor	Data Source
CyberSecurity	CMMC (Cybersecurity Maturity Model Certification)	Survey
	Cyber attack in progress	Curated
	Disaster Recovery Plan in Place	Survey
	NIST 800-171 compliance (submit to SPRS)	Survey
	Business Continuance policies and procedures	Survey
Export Controls	Export Control Status (EAR/ITAR)	Survey
	Export Control Status (Policies and procedures)	Survey
Financial Stability	Experian Intelliscore	Curated
	Financial Stability (for private companies) - Sympatic's z- score	Validated in SDX
Legal, Regulatory, Trade (LRT) Compliance	Conflict minerals	Calculated in SDX
	REACH/RoHS	Curated
	Lead Free	Calculated in SDX
	Bankruptcy	Curated
Natural Events	Earthquake	SDX RSS Feed
	Power Outage	3rd Party Source
	Tornado	3rd Party Source
	Volcano	SDX RSS Feed
	Extreme Weather	SDX RSS Feed
	Forest Fire	SDX RSS Feed
	Hurricane/Typhoon	SDX RSS Feed
	Environmental Hazard	3rd Party Source
	Flood	SDX RSS Feed
	Human Health	3rd Party Source
Man Made Events	Factory Disruption	3rd Party Source
	Factory Fire	3rd Party Source
	FDA/EMA/OSHA Action	3rd Party Source
	Force Majeure	3rd Party Source
	Mine Shutdown	3rd Party Source
	Recall	3rd Party Source
	Business Sale	3rd Party Source
	Business Spin-Off	3rd Party Source
	Company Split	3rd Party Source
	Corporate Restructuring	3rd Party Source
	Merger & Acquisition	3rd Party Source
	Port Disruption	3rd Party Source
	Profit Warning	3rd Party Source
	Protest/Riot	3rd Party Source
	Regulatory Change	3rd Party Source
	Chemical Spill	3rd Party Source

	Fine	3rd Party Source
	Geopolitical	3rd Party Source
	Price Fluctuation	3rd Party Source
	Airport Disruption	3rd Party Source
	Labor Disruption	3rd Party Source
	Labor Violation	3rd Party Source
	Leadership Transition	3rd Party Source
	Legal Action	3rd Party Source
Parts And Materials	BOM validation status	Calculated in SDX
	Life Cycle Stage	Curated
	Line of Balance Variance - orders placed vs orders forecasted	Calculated in SDX
	Material price volatility	Curated
	Production Readiness	Survey
	Quality and inspection processes	Calculated in SDX
	Rare Earth Minerals	Calculated in SDX
	Special processes	Calculated in SDX
	Material Input Lead-time	Validated in SDX
	Material-input Multi-source	Calculated from SDX
	Part Manufacturing Lead-time	Validated in SDX
	Part Multi-source	Calculated from SDX
	N-tier dependencies	Calculated in SDX
Supplier Performance	On-time delivery performance for part (all Vendors)	Customer provided
	Vendor on-time delivery by part	Customer provided
	Vendor on-time delivery performance across all parts	Customer provided
	Vendor quality rating	Customer provided
	Employee Turnover / Absenteeism	Customer provided
Customer Curated	Parts Shortage	Customer provided
	Historical Part OTD Performance	Customer provided
	Part Concession Frequency	Customer provided
	Vendor Concession Frequency	Customer provided
	On time order placement (1st tier to sub-tier)	Customer provided