Long-term Supply Chain Risks:
Scenario Planning Meets Natural Language Processing

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ABSTRACT

This project presents a next-generation risk management framework designed to proactively identify and mitigate long-term risks in the cell therapy supply chain. This framework leverages Natural Language Processing (NLP) to interpret large volumes of unstructured data from the media to create two data-driven scenarios. The model is trained on 13,377 news articles per country within the sponsor's company network from 2011 to 2024, combined with structured economic and security indicators, to forecast political risk in 2027. On the basis of the publicly available country annual risk index, our model identifies Japan as facing the most significant increase in political risk, with its index rising from 10.8/100 in 2024 to 16.2 in 2027. Two scenarios are then generated to translate risk signals into operational impact. Through simulation of local geopolitical disruption, Scenario A reveals that existing mitigation strategies are insufficient: market share would decline by 20%. Building on the disruption analysis in Scenario A, Scenario B further explores the structural vulnerabilities in the digital aspect by simulating three strategic future "worst to best" orders: a reactive, compliance-driven path; a fragmented and vulnerable system; and a secure and connected supply chain. These simulations reflect different levels of digital maturity, governance, and risk readiness. Scenario B demonstrates that transitioning to a fully integrated, secure digital infrastructure could reduce inventory holding costs by up to 25%, improve service levels by 40%, and cut recovery time by more than 50%, establishing a measurable pathway to both operational efficiency and digital resilience. Together, these scenarios emphasize the importance of proactive leadership, integrated technology, and strategic planning to build a resilient supply chain.

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Doaa Khalil

ٱلْـحَمْدُ لِلَّهِ ٱلَّذِي بِنِعْمَتِهِ تَتِمُّ ٱلصَّالِحَات

To my husband and partner, Karim. I couldn't have done this without your constant support. You believed in me when I questioned myself, encouraged me when I hesitated, and carried the weight of our life so I could chase this dream. You believed in this dream even before it became a reality, and you sacrificed so much to help make it happen. Thank you for your love, your constant belief in me, and for always being there.

To my parents, Abdelwahab and Rawhia, thank you for everything you have given to me, your strength, your sacrifices, and the values you instilled in me. Everything I’ve achieved is rooted in the foundation you gave me.

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Ngan Nguyen

To my parents, Mẹ Thu, Ba Trí. Thank you for giving me the world.

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1. INTRODUCTION

1.1. Motivation

Supply chain disruptions can have life-threatening consequences in the healthcare industry. This project focuses on the cell therapy supply chain, a sector in innovative pharmaceuticals, which is particularly susceptible to disruption because of its highly customized processes, requirement for refrigerated logistics, and time-sensitive delivery. Recent global events, such as the COVID-19 pandemic, geopolitical conflicts, and natural disasters, have further exposed the vulnerabilities of global networks.

As a result, pharmaceutical companies are placing greater emphasis on discovering more robust and proactive risk management strategies to ensure business continuity, maintain competitive advantage, and uphold regulatory compliance. Our partner company is a multinational corporation, producing cell therapy for blood cancer treatment, with its headquarters in New Jersey. With a sophisticated global supply chain spanning multiple continents, encompassing state-of-the-art manufacturing facilities and a network of suppliers, the company navigates a diverse array of risks that could disrupt its operation and mission.

These risks span a spectrum, from the rarity of pharmaceutical-grade materials to geographic instability and natural disasters to cybersecurity threats. Despite its functionality, the company's current risk management approach has several limitations. Firstly, the existing system is reactive; it primarily responds to disruptions after they occur, rather than proactively identifying and mitigating potential risks. Furthermore, the manual assessment of many risk evaluation and mitigation tasks leads to inefficiencies and potential human errors. Lastly, current static models do not adequately account for the dynamic nature of global supply chains, innovative cell therapy supply chain characteristics, and emerging risk factors.

To address these challenges, the company is seeking to develop a next-generation risk management system that leverages advanced technologies. This initiative aligns with the company's strategic goals of enhancing supply chain resilience, improving operational efficiency, and solidifying its position as an industry leader in technology.

1.2. Problem Statement

The primary objective of this project is to design and implement a comprehensive, data-driven risk management framework that will enable the partner company to proactively identify, assess, and mitigate supply chain risks across its global operations.

This next-generation system should provide real-time insights, artificial intelligence-driven capabilities, and actionable recommendations to support informed decision-making at various levels of the organization. In this context, the key questions to be addressed include

1. How can advanced analytical methods be effectively integrated to create a proactive long-term management framework to predict risk indicators?

2. What methodologies and models can be developed to accurately predict and quantify potential disruptions across different risk categories (e.g., operational, financial, geopolitical, environmental)?
3. How can we create a solution that offers our sponsor company actionable insights and recommendations for risk mitigation strategies?

1.3. Scope: Project Goals and Expected Outcomes

The overarching goal of this project is to provide the partner company with a risk management framework that enhances its ability to navigate the complexities of global supply chains in an increasingly uncertain business environment. To achieve this, we will focus on the following key areas:

1. **Risk Identification and Assessment**: Discover models that can identify potential long-term risks (3–7 years or more) across multiple dimensions, including operational and environmental factors.
2. **Data Integration**: Develop a scenario planning model that consolidates information from various internal and external sources as described in Table 1, including supplier data, market intelligence, and geopolitical indicators.
3. **Decision Support and Scenario Planning**: Develop simulation tools that allow supply chain managers to explore various "what-if" scenarios and evaluate the potential outcomes of different risk mitigation strategies.
4. **Integration with Existing Systems:** The model is a prototype, and the company will need to test the integration of the new model with its existing supply chain management, enterprise resource planning (ERP), and data repository systems to facilitate data flow and decision execution.

Table 1. Internal data gathered from sponsor company

Data Classification	Subclassification Data	Comment on importance
Risk management	Risks assessment and mitigation plan in the next 0-3 years	The company's approach to risk management will have a long-lasting impact. Being robust and adaptable will support long-term risk mitigation. This insight is foundational for understanding how vulnerable the company is to different types of future risks.
	Integrated and enterprise risk management processes, schematic process	

Supply chain mapping and planning	Overview of manufacturing and supply chain network	Such data is critical for risk identification as it helps locate bottlenecks, vulnerabilities, exposure to risks, and long-term infrastructure.
	Material and capacity planning parameters	Understanding the planning horizon helps in assessing flexibility and responsiveness to changes.
	Supplier performance	Supplier reliability and geographical risk (e.g., disruptions due to political or environmental reasons) are major considerations in long-term risk planning.

The expected deliveries for this project include:

- A comprehensive risk management framework tailored to the partner company's global supply chain operations.
- A fully functional prototype of the next-generation risk management framework, including exogenous data integration and visualization components.
- Expected set of key performance indicators (KPIs) to measure the effectiveness of the new risk management approach.
- Recommendations for implementation, change management, and ongoing system maintenance.
- Detailed documentation of the system framework developed during the project.

Upon successful implementation, the partner company anticipates significant improvements in its ability to identify and mitigate supply chain risks, leading to enhanced operational resilience, reduced disruptions, and improved supply chain performance.

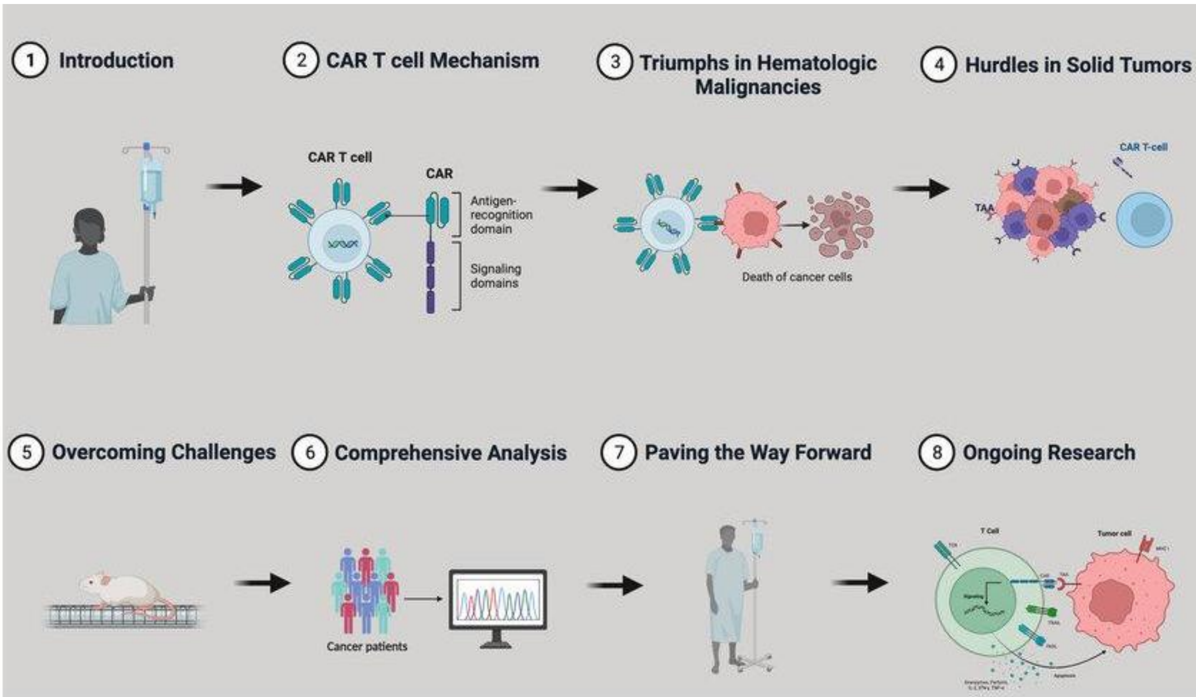
2. STATE OF PRACTICE

In this section, we will characterize the supply chain of cell therapy and subsequently explore the methodology of risk management that is currently applicable to managing its complexity. We will discuss natural language processing (NLP) and simulation-based modeling, two advanced solutions that offer opportunities to integrate with traditional scenario planning.

2.1. Generative Biopharma for Cell Therapy

Cell therapy, a vital domain of generative biopharma, involves modifying or introducing living cells into patients to treat diseases, particularly cancers. A prominent example is Chimeric Antigen Receptor T-cell (CAR-T) therapy, which engineers a patient’s T cells to express specific receptors that enable the targeted elimination of cancer cells. This personalized treatment has revolutionized oncology, particularly in addressing hematologic cancers (Fliesler, 2022). Figure 1 provides a comprehensive overview of the development and mechanisms of CAR-T cell therapy.

Figure 1. Mechanisms of CAR-T (Poojary et al., 2023)



Despite its success, CAR-T therapy faces challenges such as the difficulty of obtaining sufficient functional T cells from patients and the high cost and time required for individualized manufacturing. To overcome these barriers, researchers have made significant advancements. Harvard Medical School's Professor George Q. Daley has developed a method to use induced pluripotent stem cells (iPS cells) to produce generic CAR-T cells at scale. According to Daley, "Generic iPS cells can be converted to CAR-T cells not only more efficiently but more effectively, creating an enhanced CAR-T cell that more faithfully resembles the gold-standard clinical-grade cells we currently use. Our strategy could enable off-the-shelf CAR-T therapies and help more patients access these treatments." (Fliesler, 2022).

In parallel, Stanford Medicine has introduced a pioneering cell-based therapy for metastatic melanoma using tumor-infiltrating lymphocytes harvested from patients' tumors. These lymphocytes are grown in the lab and then given back to the patient to boost their immune system's fight against cancer cells, showing promise for better treatment of solid tumors (Conger, 2024).

2.2. Cell Therapy Supply Chain Characteristics

The development of effective supply chain strategies is critical to ensuring that these groundbreaking treatments are accessible to patients on a global scale. The uncertainty framework is a strategic approach used to analyze and address the unpredictability and variability inherent in complex systems, such as supply chains for innovative products. As described by Lee (2002), this framework helps organizations align their strategies with different types of supply and demand uncertainties, enabling more resilient and adaptive decision-making. This is relevant for cell therapy products, such as CAR-T cells, which face high demand uncertainty due to short product lifecycles, prohibitive costs, and patient-specific needs. On the supply side, the processes are often evolving and rely on emerging technologies, low and variable manufacturing yields, and a limited supply base.

By applying the "uncertainty framework," the challenges of CAR-T therapy's individualized production and high costs can be mitigated through responsive supply chain strategies. For instance, advancements like off-the-shelf CAR-T cells derived from iPSCs or tumor-infiltrating lymphocytes can shift these therapies toward more stable supply processes. These innovations reduce reliance on patient-specific cell sourcing and enable scalable, efficient manufacturing processes. Aligning the supply chain to meet the demand uncertainties of innovative therapies and addressing evolving supply conditions is essential to make these life-saving treatments more accessible, affordable, and sustainable for patients worldwide. In the next section, we will present state-of-the-practice for long-term risk management of innovative products with a high uncertainty supply chain (Lee, 2002).

2.3. Long-term Supply Chain Risk Management

Risk management has always been under the radar of corporate and supply chain professionals. However, the attention given to the topic has become unprecedentedly heightened as the world faces the COVID-19 pandemic, the Ukraine-Russia war, and US-China tension. Companies struggle to strike a balance between resilience and cost as the economy is recovering from a recent crisis. Nevertheless, the rapid advent of artificial intelligence has brought about opportunities and novel applications for risk management methodologies to evolve.

This section begins to examine the fundamentals of a risk management framework that includes four stages: risk identification, risk assessment, risk mitigation, and risk resilience (Emrouznejad et al., 2023). Risk identification is the process of mapping the current supply chain design with factors or events that potentially create threats to the operation of the company. The source of input data often relies on monitoring the news, industrial trends, or market reports. Risk assessment involves projecting the likelihood of the risk materializing and the severity of the impact it consequently has on the company. Common techniques in industry are Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis, and Business Impact Analysis (BIA). Next, risk mitigation entails defining and implementing preventive measures to eliminate or reduce the identified risk. This stage often translates into a Business Continuity Plan (BCP), which cascades throughout the organization. The effectiveness of a company’s risk management can be assessed with metrics such as Time to Recovery (TTR) and Time to Survive (TTS). Lastly, risk resilience is a cycle of observing and assessing vulnerabilities to continuously build capabilities and reduce susceptibility to disruptions (Revilla et al., 2023).

PESTLE is an acronym for political, economic, social, technological, legal, and environmental factors. PESTLE provides a comprehensive lens for evaluating external risks. This framework remains a cornerstone for strategic environmental analysis and was first introduced in Francis J. Aguilar's 1967 book Scanning the Business Environment.

The PESTLE framework has significantly evolved since its inception, becoming integral to strategic decision-making across various industries. Recent advancements have enhanced its analytical depth and predictive capabilities.

At present, our sponsor company has adopted the above principles with the Integrated Risk Management (IRM) and Enterprise Risk Management (ERM) framework. This implementation of IRM and ERM shifts away from a siloed approach where individual functions manage their unique risks independently. Hence, IRM and ERM enable consistency at the corporate level, enhance visibility to internal risk concentration, and coordinate optimal mitigation strategies. The company is currently outsourcing the process of collecting information to third-party intelligence services. However, these services tend to focus on short-term risk, typically spanning from months to within a year or two. Moreover, the dynamic and volatile nature of risk leads to an overwhelming volume of information. As a result, such reports fail to deliver proportional value to the company, as executives find them scattered and lacking prominent trends from which they can extract actionable insights.

Next, we will explore analytical techniques to assist with the steps outlined in the aforementioned risk management framework.

2.4. Natural Language Processing (NLP)

First, we look at Natural Language Processing (NLP) for risk identification, which taps into the resources of the media. This approach is a more efficient way to extract relevant information for insightful trends.

NLP is a subfield of artificial intelligence (AI) that enables computers to interact with human language by reading, recognizing, and interpreting texts or speech. Significant advancements have been made in the field of NLP, as a plethora of applications have been developed, such as sentiment analysis, pattern recognition, speech recognition, and translation. With relevant and appropriate adaptations, these tools can shape how unstructured data are collected and analyzed to influence supply chain decision-making (Jackson et al., 2023).

Sentiment analysis is gaining popularity and is well-developed as one NLP technique. The method involves extracting verbatims to derive opinions, emotions, and attitudes towards a particular topic. Companies increasingly employ it to track and review customers' ratings and remarks about their products and services (Saad & Saberi, 2017). By using text mining with NLP, patterns and trends can emerge that might not be immediately apparent in the form of words or databases.

Semantic search, when combined with sentiment analysis, is a powerful technique in risk identification. This searching technique aims to retrieve information based on an understanding of context and the intent of the user's queries, rather than relying solely on exact keyword matching like traditional search engines do (Saad & Saberi, 2017).

While creating an NLP model from the beginning is ideal to govern the source of data used for model training, it is data-intensive, resource-consuming, and computationally demanding. For the scope of this project, we will utilize the readily available Application Programming Interface (API). API is a set of functions, classes, and modules that have been built by developers and are customizable by contextualizing our input variables. Natural Language Toolkit (NLTK), a Python-based package that works with human language data, offers the ability to perform the sequencing of NLP processing tasks shown in Figure 2. Sequencing NLP ensures that the model captures the correct order and relationships between words, which is critical for accurately understanding, generating, or translating language.

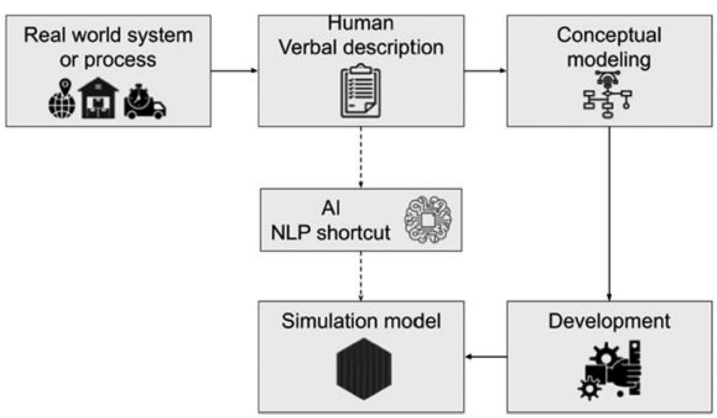
Figure 2. Key steps in NLP (IBM, 2024)

Step 1: Text processing	Step 2: Text extraction	Step 3: Text analysis	Step 4: Model training
• Transforms original text to a computer-readable format. • Begins with tokenization, which breaks the text into smaller units, such as words or phrases, simplifying complex text into manageable chunks.	• Converts textual elements into numerical representations, enabling machines to analyze and decipher the data.	• Employs dependency parsing to identify grammatical relationships and understand sentence structures, and sentiment analysis to assess the emotional tone, categorizing it as positive, negative, or neutral.	• Trains model to identify patterns and correlations within the data. • Generates predictions or outputs for new, unseen text. • Undergoes continuous refinement through evaluation, validation and fine-tuning for real-world applications.

2.5. Simulation-based Supply Chain Risk Modeling

Simulation models address the limitations of traditional analytical models by encapsulating the nonlinearity, unpredictability, and complexity of an interconnected supply chain. Volatile variables like unpredictable demand, inconsistent lead times, different inventory strategies, and rare events called "black swans," as explained by Taleb (2007), can provide valuable insights and practical advice to executives when shown through simulation models (Jackson et al., 2023). Figure 3 illustrates how the NLP and API workflow arrives at simulation models as compared to traditional modeling methods.

Figure 3. Traditional workflow versus NLP utilization (Jackson et al., 2023)

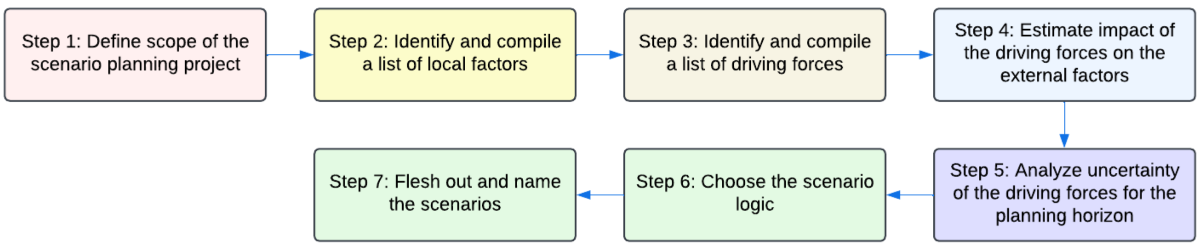


2.6. Scenario Planning

Scenario planning is a strategic approach that adopts an "open systems" perspective, acknowledging the influence of external environments—such as geopolitical events, stakeholder demands, media, natural phenomena, and organizations' strategic decisions. By gathering and analyzing relevant data, scenario planning develops comprehensive sets of scenarios that depict macro environments the organization might face, enabling proactive and adaptive strategic decision-making (Phadnis et al., 2022).

The MIT Center for Transportation and Logistics (CTL) Scenario Creation Framework provides a structured method for planning (Figure 4) under uncertainty by distinguishing between controllable decisions and uncontrollable external forces to enable effective preparation and contingency planning.

Figure 4. Generic scenario creation process (Phadnis et al., 2022)



Despite the growing complexity of the cell therapy supply chain, current risk management practices remain limited in their ability to address long-term uncertainty. The uncertainty framework highlights the need for differentiated strategies based on supply and demand characteristics, yet its application to cell therapy is underutilized. The company currently relies on established tools such as Integrated Risk Management (IRM) and Enterprise Risk Management (ERM), but these are typically short-term in focus and lack the foresight needed for strategic decision-making. Meanwhile, advanced analytical approaches such as Natural Language Processing (NLP) offer a scalable method to extract early warning signals from unstructured media sources. Furthermore, simulation-based supply chain modeling provides deeper insight into system-level weaknesses. However, these tools are not yet fully integrated into a structured approach for scenario planning, which is essential for anticipating and preparing for a range of long-term futures. Together, these gaps highlight the need for a more proactive, data-driven strategy for long-term risk identification, scenario planning, and mitigation tailored to the unique challenges of cell therapy.

3. METHODOLOGY

In this section, we will present the development and selection of our methodology framework, which integrates both internal and exogenous factors. Then, each step in the framework will be elaborated and discussed in detail.

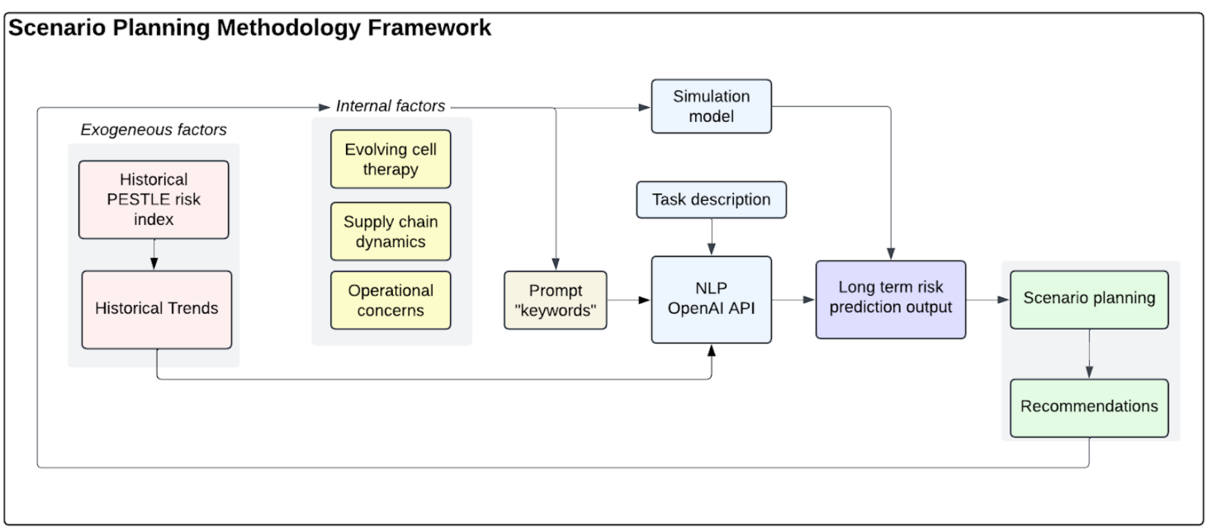
3.1. Selection of Methodology

Our methodology, shown in Figure 5 below, employs a structured scenario planning approach to tackle the long-term risk management challenges of our sponsor company. By integrating the PESTLE framework explained in Section 2.3 with advanced tools like NLP and simulation modeling, this approach enables a thorough analysis of internal and external factors. The goal is to generate plausible scenarios and actionable recommendations to support strategic decision-making.

We chose this methodology for its ability to combine qualitative insights with data-driven techniques, ensuring a comprehensive evaluation of risks. The framework provides a robust foundation for assessing chosen external factors, while NLP and simulation modeling offer advanced capabilities for trend analysis and scenario generation. This hybrid approach is well suited for addressing the complexity and uncertainty inherent in long-term risk management.

For instance, integrating machine learning and natural language processing (NLP) allows for the analysis of extensive data sources, such as news articles and social media, facilitating a dynamic assessment of external factors. Additionally, hybrid modeling approaches that combine PESTLE analysis with simulation techniques have emerged, providing a more comprehensive understanding of complex, interconnected risks. These methodologies enable the simulation of various scenarios, aiding in robust decision-making and strategic planning. (Fakhimi & Mustafee, 2024).

Figure 5. Scenario planning methodology framework for this project



3.2. Framework Explanation

Step 1: Define Exogenous Factors from Historical Trends and External Risk Inputs

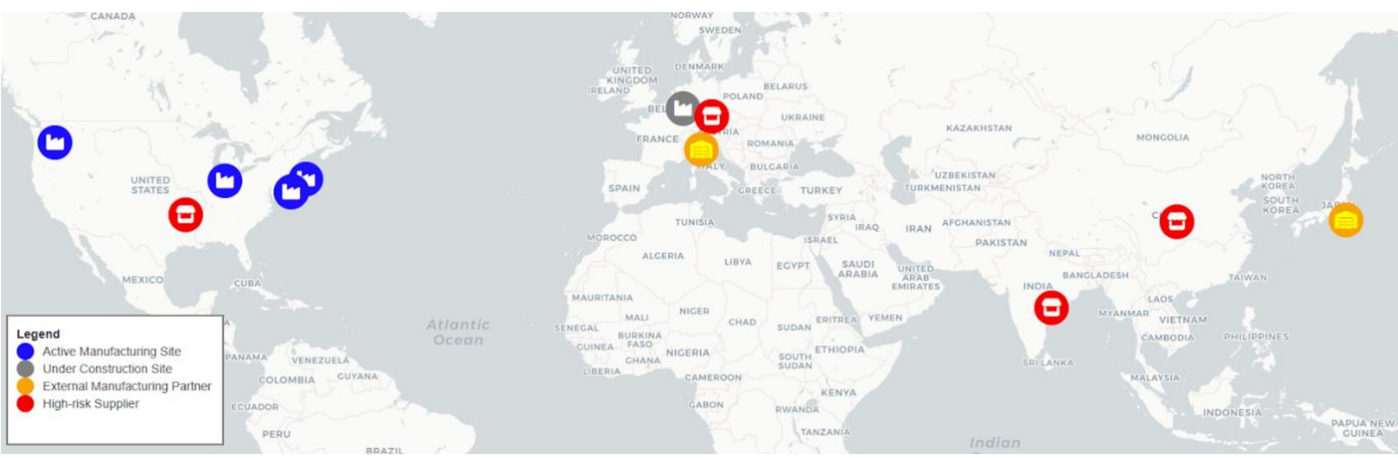
The two key inputs at this step are the historical PESTLE risk index and historical trend data. For our sponsor company, possible risks to be discovered and simulated include a geopolitical crisis in a facility's location disrupting global trade, financial instability of key suppliers, and global risk trends influencing the supply chain. Historical external trends are captured through sources like the BMI Country Risk Index and structured news analyses. These driving forces provide a comprehensive foundation for identifying and understanding critical risks and opportunities.

Step 2: Define Internal Factors from Operational and Supply Chain Inputs

After defining the scope, the first step in a scenario project involves thoroughly analyzing the partner company's environment to identify local factors influencing external risk decisions. For our sponsor company, this process includes supply chain network mapping (depicted in Figure 6) to examine the structure and dependencies of their supply chain, as well as sourcing data to assess procurement strategies. Through this analysis, we identified four single-source high-risk suppliers that are exposed to external risks. To address scalability challenges, their next innovation "Project.C" project, focuses on automating the current manual production processes, autonomous in replenishment and supply planning, and expanding operations by establishing new plants in diverse regions. Finally, a comprehensive evaluation of current risk management practices was conducted, examining internal risks in terms of their impact, likelihood, exposure, and control measures. This thorough assessment ensures a clear understanding of local factors that shape risk decisions.

We reviewed the existing backup plans and found that the organization has a robust strategy for substituting plants and an additional protective layer with high safety stock levels, capable of sustaining operations for up to six months. Additionally, semi-structured interviews with participating teams provide valuable qualitative insights and diverse perspectives. These findings collectively highlight critical factors that influence decision-making and showcase the organization's preparedness for potential disruptions.

Figure 6. Current supply chain network



Step 3: Compile and Translate Driving Forces into Simulation Inputs

Driving forces are macro-level aspects of the business environment. They affect the organization through multiple local factors. External driving forces are systematically compiled using historical indices and NLP-based trend extraction. Our scenario planning base model will rely on external sources of the Country Risk Index and reported news.

Step 4: Build Simulation Model and NLP Integration

A focal decision is a decision about organizational action or structure within the organization's control. To estimate the impact of driving forces on the focal decision, we follow a structured, qualitative approach comprising three key substeps. First, the team assesses the influence of various local factors on the focal decision. The second part of the analysis assesses how much each driving force affects these local factors. Finally, the degree of association between local factors and driving forces is determined.

In our analysis, we leverage natural language processing (NLP) to extract insights from news and academic sources, enabling us to predict emerging trends. Additionally, we incorporate historical data, such as the BMI Risk Index, as training and testing inputs to refine and validate our predictions. This combination of qualitative evaluation and data-driven techniques ensures a comprehensive understanding of the driving forces shaping the focal decision.

Step 5: Generate Long-Term Risk Prediction Output

In the second part of our approach, we assess the uncertainty of driving forces by gathering expert predictions through interviews, industry reports, and publications, ensuring diverse perspectives. Key insights and keywords identified from these expert inputs are integrated into our natural language processing (NLP) model, enhancing its ability to analyze and predict trends. Based on the degree of expert agreement, driving forces are classified as either predictable trends or uncertainties, with plausible extreme values estimated for uncertain forces to inform scenario planning.

Step 6: Scenario Planning Based on NLP and Simulation Outputs

The scenario creation process leverages the assessed impact and uncertainty of driving forces to define scenario axes, focusing on those with high uncertainty and high impact. Using these axes, scenarios are formed by combining extreme values of key driving forces, ensuring plausible and diverse scenarios for strategic decision-making, which integrate into our simulation-based approach for scenario planning. This step aligns with our model by systematically incorporating internal and external risk factors, processed via NLP, into simulation modeling for robust scenario generation and tailored recommendations.

Step 7: Recommendations Development and Scenario Narratives

The last step involves crafting narratives for each scenario, integrating the specified driving forces into a cohesive future business environment, a plausible pathway from the present, and a memorable scenario name.

For example, scenarios could include a geopolitical crisis in Japan disrupting supply chain continuity, a financial risk impacting key suppliers, or an accelerated shift to regional manufacturing due to environmental regulations. Additionally, leveraging NLP tools to analyze external risk trends and integrating internal factors such as organizational risk controls and supply chain network design plans can enhance the scenario's relevance and accuracy, aligning with our approach to provide strategic insights and actionable recommendations.

4. RESULTS AND DISCUSSION

In this section, we begin by outlining the development and interpretation of the NLP-based prediction model. The procedure includes the integration of sentiment data extracted from news sources with structured risk indicators to train and interpret a machine learning model. Following this, we generate two major forward-looking scenarios with various forward-looking sub-scenarios, informed by the model’s outputs and qualitative insights gathered from interviews with the sponsor company. These scenarios serve as the foundation for scenario planning and mitigation plan recommendations to the sponsor company.

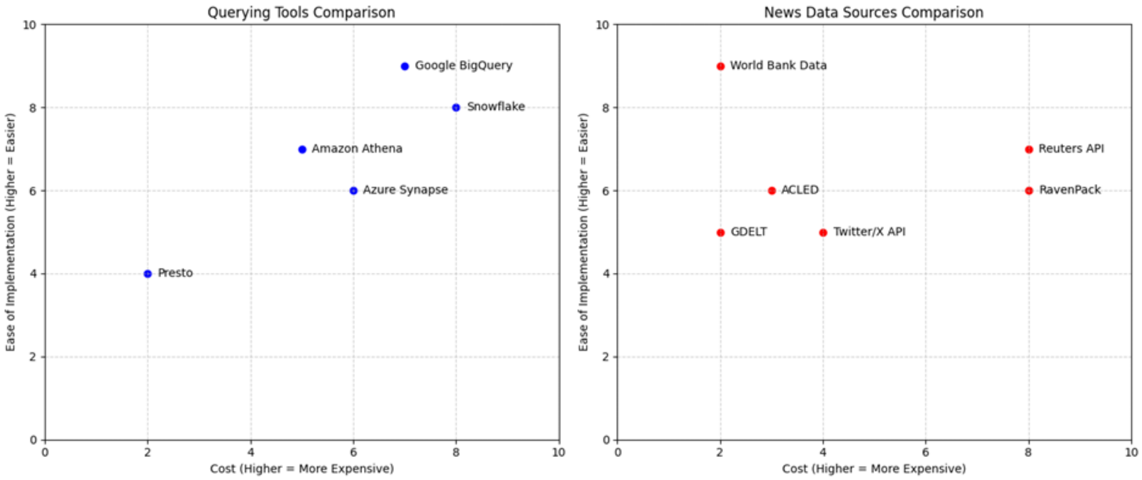
4.1. NLP— ML Model

The four primary processes of the NLP model are as follows: querying unstructured news data, choosing features, developing a machine learning model, and, finally, predicting a future target variable. The following discussion centers around the key considerations for each step, output, challenges faced during the process, and recommendations for scale-up from the pilot.

4.1.1. Querying unstructured news data

In this step, it is essential to identify the querying tool and news sources for gathering unstructured data. The criteria for selection are the ease of implementation and the cost of accessing the data. Ease of implementation entails the ability to process both structured and unstructured data, speed of query, scalability infrastructure, and maintenance. Our model requires over 10 years of data for robustness, global coverage, and, ideally, real-time updates for practicality when scaling up. Figure 7 presents multiple options.

Figure 7. Cost and ease of implementation between different tools (left chart) and news sources (right chart). Own work.



After evaluating various alternatives against the criteria, Google BigQuery and Global Database of Events, Language, and Tone (GDELT) emerge as the optimal combination for our model. GDELT offers free, real-time translated news from media sources around the world. Furthermore, GDELT is designed and optimized to work with Google BigQuery, hence, this combination performs efficiently and is suitable for the pilot.

Next, the query retrieves country-related news using geographical keywords like Japan, China, the Netherlands, and India. These are derived from the sponsor company's facility network. Our model returned a total of 13,377 news articles per country from 2011 to 2024. This value averages 2.6 news articles per day. We find this number reasonable and practical, considering computational running time and the need to control the risk of introducing noise to the model by overfeeding.

4.1.2. Features and targets

This step involves processing the features as input for predicting the risk index of a targeted country. Two features introduced into our model are news sentiment and a transformed combination of economic and security risk.

First, the news dataset retrieved in the query is processed by Hugging Face with a FinBERT model. This pre-trained NLP combination performs deep learning-based sentiment analysis, which is superior to traditional models such as VADER and Textblob when it comes to contextualizing risk-related content. Deep learning-based sentiment analysis refers to the ability to comprehend attitudes and emotions through context rather than just words. Meanwhile, SpaCy and PyTorch were also under consideration. However, these packages lacked various pre-trained models, making it difficult for the company to implement and scale. Hence, Hugging Face is the selection for our model.

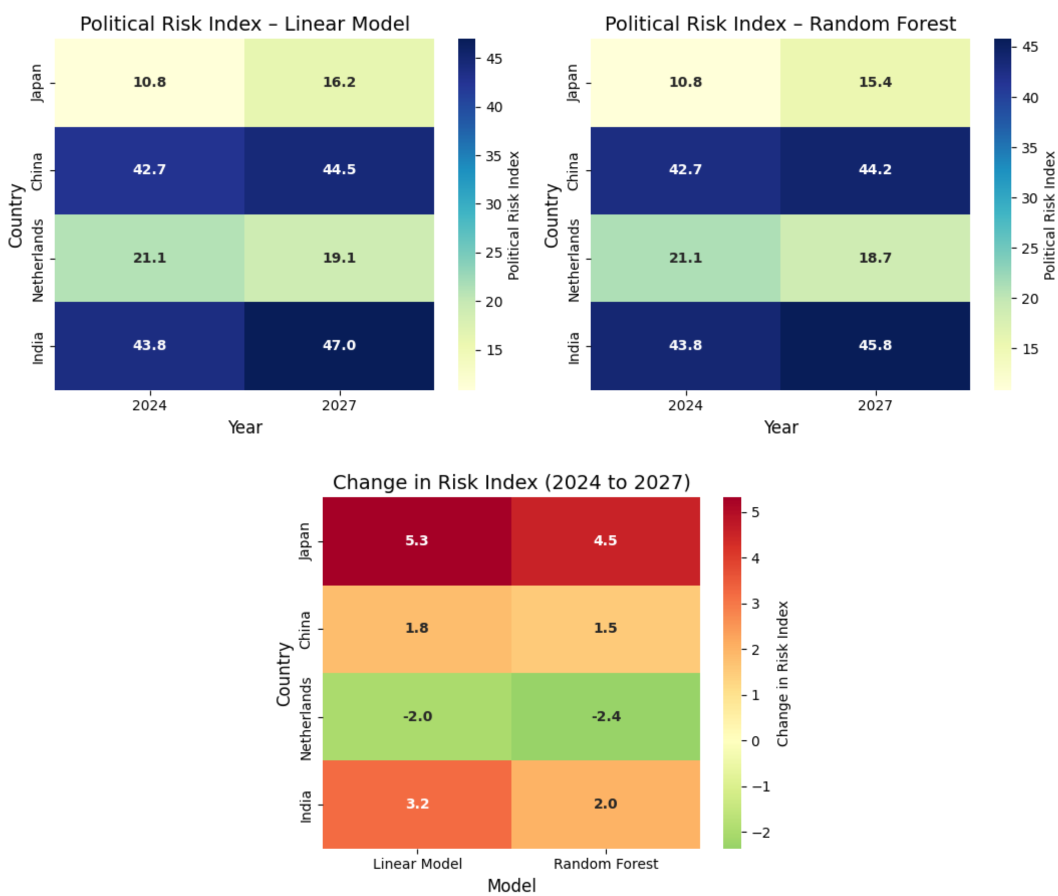
For long-term risk prediction, sentiment score is introduced as a lead feature. The lead period is selected to be 3 years, which aligns with the purpose of projecting long-term risk for strategic planning. This feature is represented as Sentiment_lag3 in subsequent evaluation of the model.

The second feature is the output of Principal Component Analysis (PCA) from the economic and security risk index, represented as PCA_Risk in the model. The dataset of the country's risk index is sourced from BMI Fitch Solutions, which is a multinational country research firm. The risk index in this dataset ranges from 0 to 100, with lower values indicating lower risk and vice versa. The rationale behind integrating economic and security factors in the model is that political, economic, and security factors are often interdependent and influence one another.

4.1.3. Machine learning model for prediction

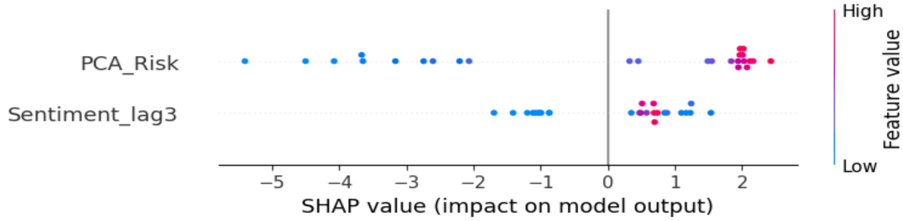
In this step, the machine learning model is trained to map the 3-year lead news sentiment and the economic-security risk index to the political risk index. The prediction from the model in Figure 8 reveals shifts in political risk across Japan, China, the Netherlands, and India. Notably, Japan experiences the most substantial increase, with its index rising from 10.8 in 2024 to 15.4 under the Random Forest model and 16.2 under the Linear Model. In contrast, other countries show less pronounced changes. The random forest and linear models provide complementary insights, with both indicating Japan's risk increase as the most significant among the countries studied.

Figure 8. Prediction and change in risk index identified by our model (Simulation ran in February 2025)



The SHAP (Shapley additive explanations) in Figure 9 highlights the role of both PCA_Risk and Sentiment_lag3 in shaping the prediction of political risk. While PCA_Risk shows a broader and more dominant influence, the impact of Sentiment_lag3 reveals a consistent and meaningful pattern. Specifically, negative or pessimistic tones in news coverage over the past three years are associated with higher predicted political risk. This suggests that the model is sensitive to long-term sentiment trends. Although the overall contribution of sentiment is smaller than PCA_Risk, it is clear directionally that a sustained negative tone in geopolitical news increases the model's forecast for political instability. This aligns with our hypothesis that sentiment extracted from news can serve as a forward-looking signal for emerging political risk.

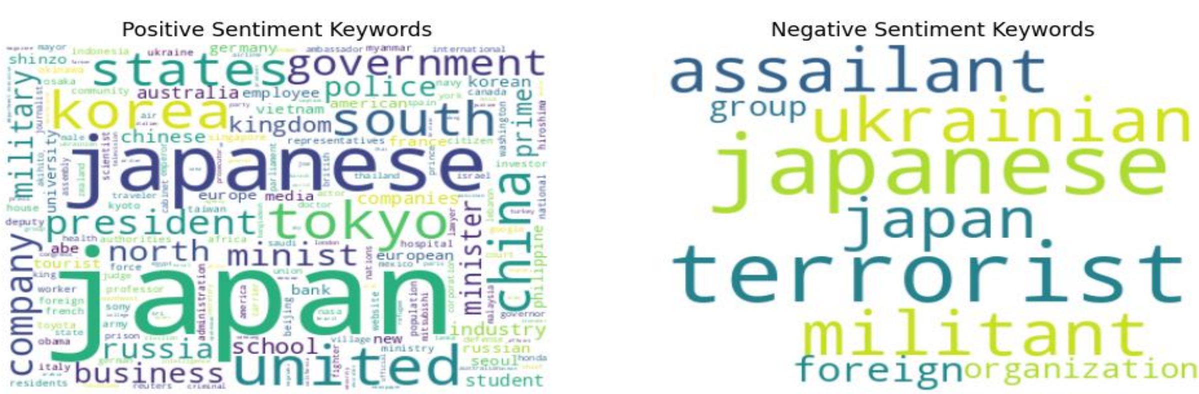
Figure 9. SHAP value of the two features on the model (Simulation ran in February 2025)



4.1.4. Prediction of risk index in the next 3 years

The word cloud output in Figure 10 illustrates the sentiment-driven keywords extracted from news data, which form the basis for forecasting potential risks for Japan in 2027. On the positive sentiment side, dominant terms such as *government*, *president*, and *business* reflect frequent mentions of institutional actors and national affairs. Terms like *United*, *Korea*, and *South* suggest regional or international associations. In contrast, negative sentiment features terms such as *terrorist*, *militant*, *assailant*, and *foreign*, along with *Ukrainian*, pointing to themes of conflict and insecurity. Notably, some terms appear in both clouds, underscoring that sentiment classification is context-dependent and influenced by tone, proximity to other keywords, and narrative framing within each article.

Figure 10. Keywords which influenced risk prediction in Japan (Simulation ran in February 2025)



4.1.5. Monitoring of daily risk at facility locations

Further utilizing the capabilities of NLP, we modify the query to dynamically assess which facility locations are disrupted or available as backup options. By analyzing daily updates linked to each facility's geographic location, we can detect signals of disruption such as port closures, labor strikes, natural disasters, or political unrest. Facilities exceeding a predefined risk threshold, which are assumed for demonstration purposes in Figure 11, are classified as disrupted, while those below the threshold remain operational. This reactive capability complements proactive de-risking strategies, such as supply network redesign and inventory reallocation, by providing timely, location-specific risk visibility (Sáenz & Revilla, 2014).

Figure 11. Print out of daily risk monitoring query (Simulation ran in March 2025)

```
  Updated Facility Risk Levels:
  Facility_ID    Location       Risk_Score      Operational_Status
0 Facility 1     Location 1     0.000000        Running
1 Facility 2     Location 2     0.000000        Running
2 Facility 3     Location 3     0.000000        Running
3 Facility 4     Location 4     0.000000        Running
4 Facility 5     Location 5     0.000000        Running
5 Japan          Japan          9.653462        Disrupted

  Facility Japan (in Japan) is disrupted
  Suggested Alternative: Facility 2 in Location 2
```

4.2. Scenario Generation

Following the identified limitations in current risk management practice, the next section introduces two main forward-looking scenarios designed to inform strategic planning, which include several sub-scenarios and what-if simulations. These scenarios address both external and internal sources of uncertainty within the cell therapy supply chain. Scenario A simulates a potential disruption in Japan, based on political risk signals derived from NLP-ML analysis of unstructured news data. Scenario B explores the key capabilities required to have smart supply chain digitization, derived from the sponsor company's future vision regarding process automation, and reflects technology shifts in the organization. Together, these scenarios offer insights to support long-term resilience and decision-making at the enterprise level.

4.2.1. Scenario A: Japan Supply Chain Disruption Driven by Political Risk Model Output

This scenario integrates the output of the NLP-based political risk model, which forecasts Japan as the country most likely to experience elevated political instability out of the countries within the sponsor's company network in 2027. To evaluate the operational and financial implications of this signal, a simulation was developed to assess the impact of a Japan-specific disruption on the sponsor company's global manufacturing network.

A.1. Simulation Design Methodology

As proposed in our Scenario Planning Methodology Framework, the simulation model serves as a key mechanism to translate exogenous risk signals and internal factors into operational impact. A discrete-time simulation is developed in Python to represent the impact of a site-specific disruption over a 12-month horizon. The model incorporates site-level constraints such as production capacity, inventory buffers, staffing availability, and financial outcomes.

Disruption modeling

The simulation assumes a full operational shutdown at the Japan plant between months 6 and 8, simulating a severe political event that halts manufacturing and exports. The shock is localized to Japan but triggers redistribution and response across the entire network.

Time to Survive (TTS) and Time to Recover (TTR)

The simulation adopts Time to Survive (TTS) and Time to Recover (TTR) metrics from Simchi-Levi et al. (2014, 2015). TTS is defined as the number of months a facility can continue operating without resupply or reallocation. TTR represents the number of months required to restore full operational capacity after a disruption ends. These two parameters structure the cascading logic of shutdown and recovery across the supply network.

Redistribution logic and assumptions

During the crisis, Japan's unmet production is redistributed proportionally across other plants, based on available capacity. Redistribution is constrained by each plant's TTS, staffing levels, and throughput ceilings. Recovery ramps up linearly beginning in month 9 and is plant-specific based on TTR.

Performance metrics

The simulation tracks monthly Key Performance Indicators for:

1. Staff utilization over time
2. Fulfilled Capacity Over Time
3. Unmet demand and redistribution limit
4. Fill rate (percentage of customer demand fulfilled)
5. Revenue (volume × margin)
6. Market share (relative customer retention)
7. Inventory levels (site-specific depletion and rebuild)
8. Per-unit cost (crisis escalation and normalization)

Model implementation

The simulation is built using NumPy, matplotlib, and folium and applies custom algorithms for patient redistribution, inventory drawdown, capacity constraints, and KPI output. The output illustrates how scenario planning integrates within the broader framework to translate risk signals into actionable strategic insights.

A.2. Simulation Results and Scenario Narrative

Staff Utilization Over Time

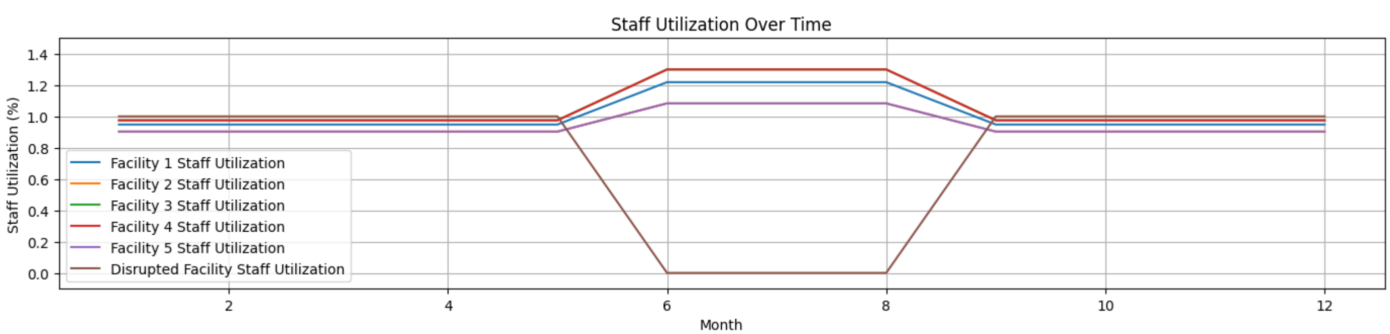
Figure 12 illustrates staff utilization across all production sites over a 12-month horizon. During the baseline stability period (months 0–5), all sites operated near steady-state utilization, around 90–95% of their available staffing capacity. Staff loading was balanced across locations under normal operational conditions, indicating efficient but not excessive resource usage.

During the crisis phase (months 6–8), Japan's staffing utilization dropped sharply to 0%, simulating a modeled full-site operational shutdown, such as could occur due to a natural disaster or geopolitical event. In response, other facilities exhibited increased staff utilization, surging up to 120–130% of their nominal staffing levels. This temporary surge reflects efforts to stretch operational capacity through overtime, resource reallocation, and intensified operations.

As recovery commenced in months 9–12, staffing levels at all sites gradually returned to baseline. Japan reactivated its workforce around month 9, and U.S. sites correspondingly normalized their staffing levels, reversing the crisis-driven surge.

This pattern underscores staff availability and represents a strategic constraint in personalized cell therapy manufacturing. Unlike automated industries, where production can scale rapidly, scaling operations dependent on skilled human operators require extended recruitment and retraining time, introducing systemic vulnerability during disruptions.

Figure 12. Staff utilization over time



Fulfilled Capacity Over Time

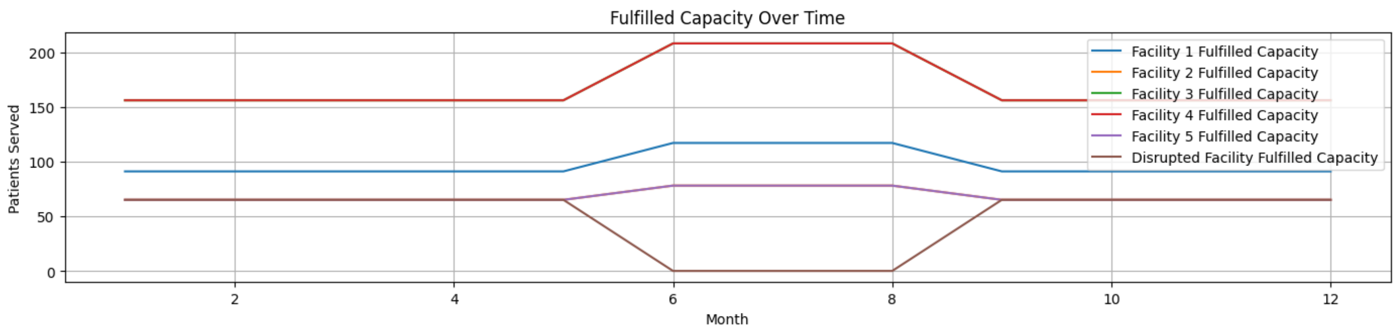
Figure 13 presents fulfilled production capacity, measured in patients served per month, across the same 12-month timeline. Under normal conditions (months 0–5), all sites maintained stable production outputs, with Japan contributing significantly to overall system throughput.

Following the disruption (months 6–8), Japan's production collapsed to zero, mirroring its staffing loss. Other sites were partially compensated for by increasing their fulfilled capacities; however, the overall system experienced a noticeable dip in total patient treatments fulfilled per month. Despite local surges, the global capacity shortfall could not be fully recovered during the crisis period.

In the recovery phase (months 9–12), Japan gradually resumed operations, restoring part of the lost system capacity. As Japan's output increased, other sites correspondingly reduced their temporarily elevated fulfilled capacities and returned to pre-crisis levels.

This fulfilled capacity trajectory illustrates the systemic rigidity of the manufacturing network under labor dependency. Capacity recovery lagged the crisis due to the time needed for operator ramp-up, and site-to-site flexibility was constrained by physical infrastructure limits and regulatory requirements.

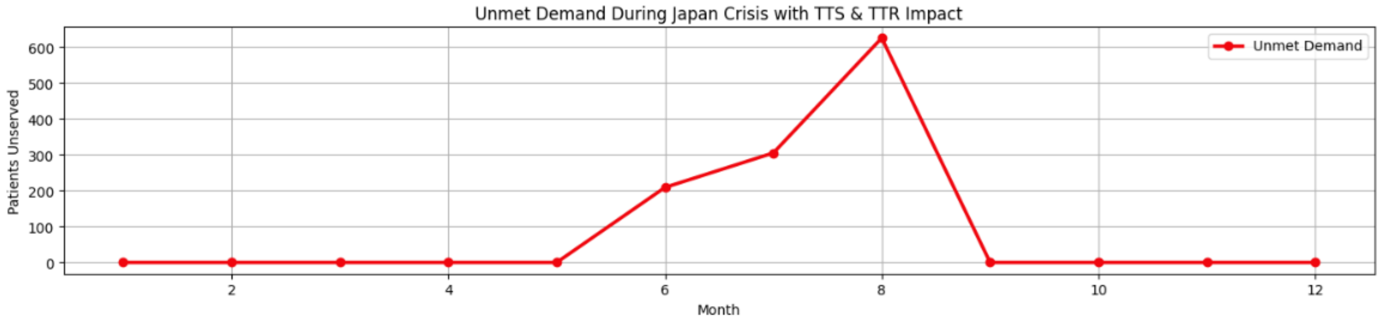
Figure 13. Fulfilled Capacity Over Time



Unmet demand and redistribution limit

The simulation results, displayed in Figure 14, highlight the escalation of unmet patient demand following the disruption of the Japan facility. During the pre-disruption phase (months 0–5), unmet demand remained effectively at zero, indicating the system's capability to meet all patient needs under stable conditions. However, starting in month 6, unmet demand volumes began to rise sharply, peaking at approximately 620 unserved patients by month 8. Although redistribution efforts partially mitigated the shortfall, alternative sites lacked sufficient surge capacity to fully absorb the disrupted volume. Recovery commenced in month 9, and unmet demand returned to near-zero levels by month 10. The temporary failure to meet patient needs underscores the operational vulnerability in manual, labor-intensive production environments where scaling during crises is highly constrained.

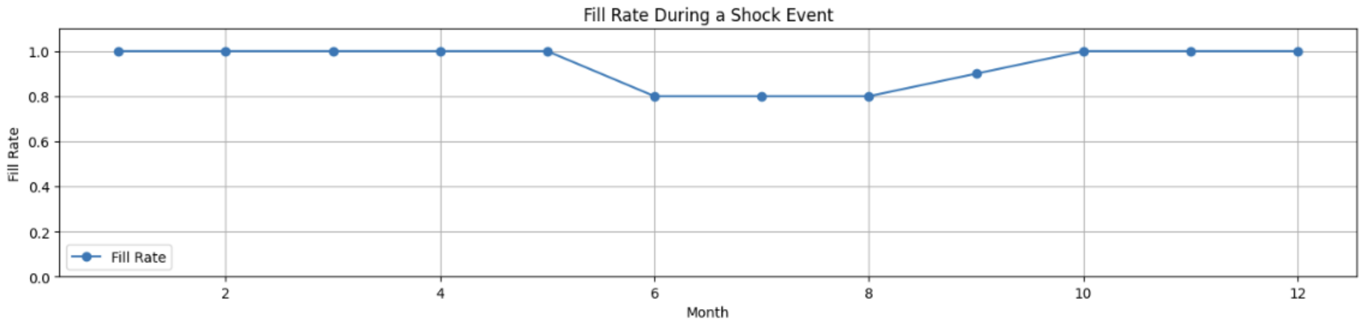
Figure 14. Total unmet demand during disruption period



Fill Rate Dynamics

As shown in Figure 15, the fill rate across the Japan market experienced significant but partial degradation following the disruption. During the months 0–5, the fill rate remained consistently around 100%, confirming stable fulfillment performance. After the operational disruption in month 6, fill rates dropped to approximately 80%, where they remained suppressed through month 8. A gradual recovery began thereafter, with fill rates reaching approximately 90% by month 9 and eventually returning to full 100% levels by month 10. This partial and delayed recovery highlights the limited resilience of the current operational model, where even moderate disruptions result in multi-month service degradation despite redistribution attempts.

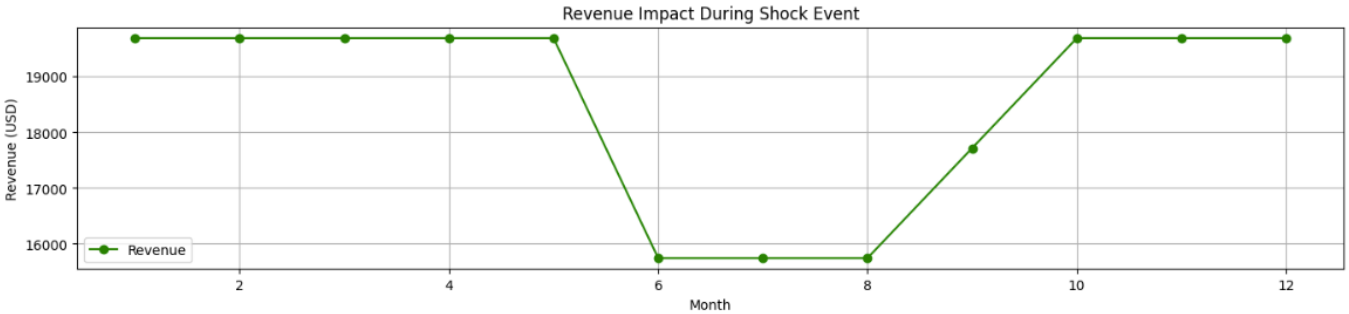
Figure 15. Fill rate over 12-month period in Japan



Revenue Impact

Revenue performance, depicted in Figure 16, closely mirrored the observed fill rate dynamics. Prior to the crisis, monthly revenues hovered around 19,600 USD. Following the disruption in month 6, revenue sharply contracted to approximately 16,000 USD, maintaining this depressing level through months 7 and 8. Revenue recovery initiated in month 9, aligning with the improvement in operational output, and was fully restored to baseline levels by month 10. Although recovery was ultimately achieved within the 12-month window, the multi-month loss in revenue reflects both the immediate financial impact of operational disruptions and the lagged recovery trajectory even after capacity restoration efforts began.

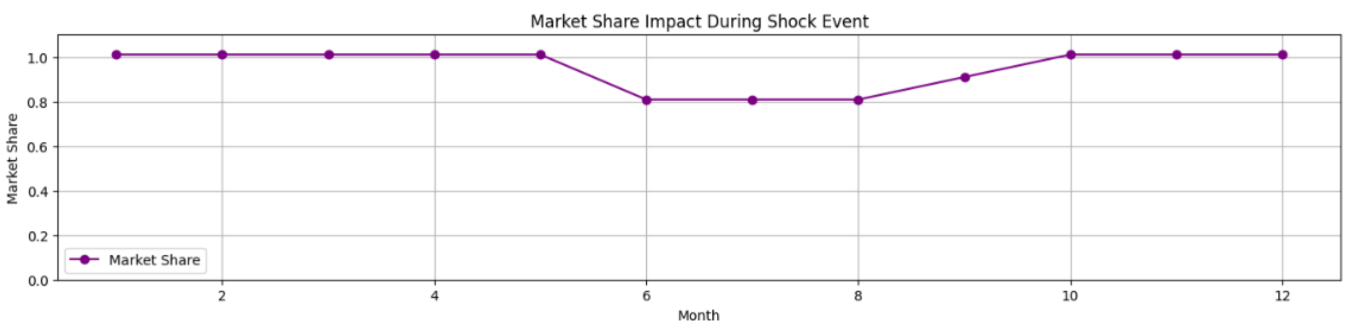
Figure 16. Monthly revenue trend in Japan



Market Share Recovery

Strategic impacts of the disruption are shown in Figure 17, which tracks market share performance. Prior to the disruption, market share within Japan and the broader Asia-Pacific region was stable at approximately 100%. The loss of service capability following month 6 triggered a rapid decline in market share to approximately 80%, where it stagnated through months 7 and 8. A gradual recovery process began in month 9, with full restoration of pre-crisis market share by month 10. While the market share recovery was ultimately successful, the vulnerability to competitive displacement during temporary service gaps remains a critical strategic concern for the company's long-term market positioning.

Figure 17. Market share loss and partial recovery



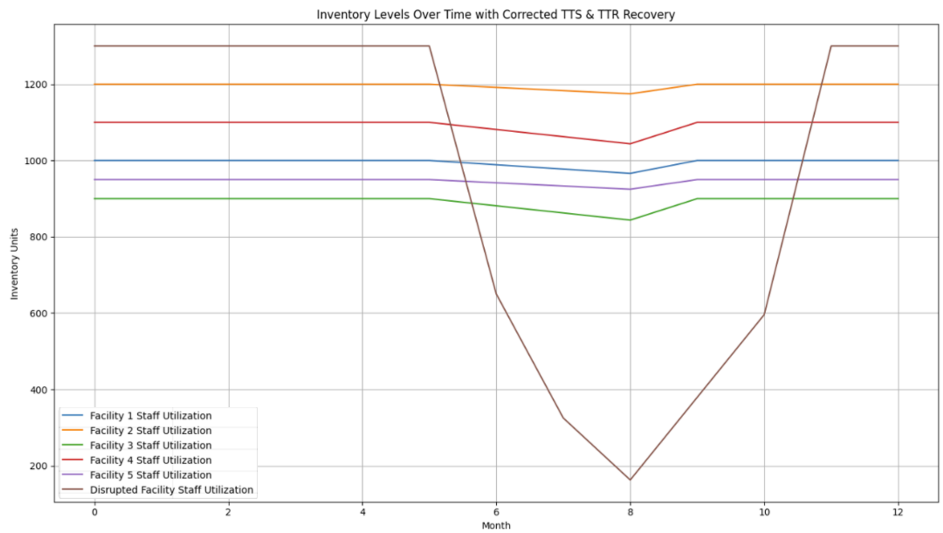
Inventory depletion and recovery

Figure 18 displays the inventory levels across all manufacturing plants throughout the disruption period. Prior to the disruption, inventory levels remained stable across all sites, with Japan maintaining the highest reserve.

Following the operational shutdown in Japan in month 6, its inventory depleted sharply, reaching a near-complete exhaustion by month 8. Simultaneously, inventory levels at Libertyville and Summit sites declined significantly due to increased redistribution demands, reflecting the stress placed on alternative nodes.

Although restocking efforts commenced around month 9, recovery was uneven across sites and remained site-dependent through month 12. This behavior highlights that static inventory buffers offer only short-term protection; under sustained disruption and redistribution pressure, they are rapidly exhausted without dynamic replenishment strategies.

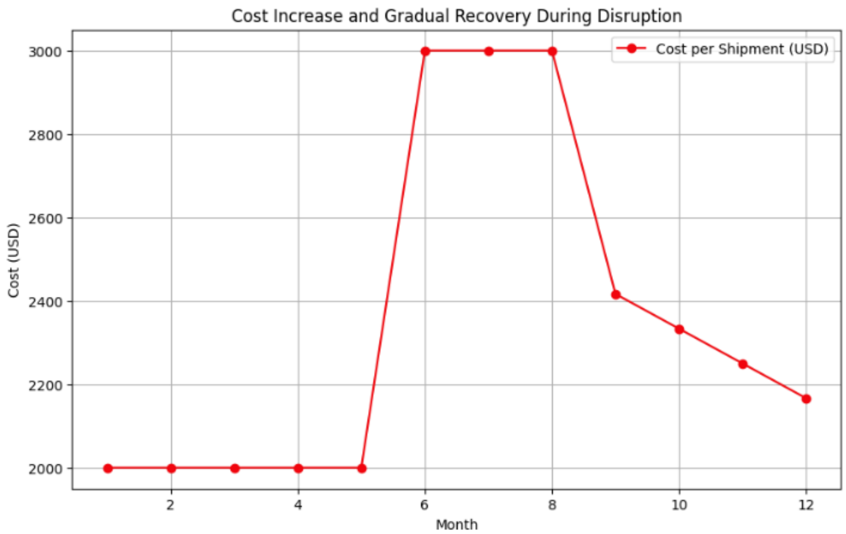
Figure 18. Inventory trajectories by site



Cost volatility

Figure 19 illustrates the escalation of per-unit shipment costs during the disruption period. Baseline costs remained stable at approximately 2,000 USD per shipment during normal operations. Beginning in month 6, coinciding with the Japan facility shutdown, costs surged sharply to around 3,000 USD per shipment, representing a 50% increase. This spike was driven by expedited logistics requirements, emergency sourcing from alternative suppliers, and labor overtime necessary to maintain production. Post-crisis, cost normalization occurred gradually over a four-month period, reflecting the system's delayed ability to stabilize operations and renegotiate sourcing and logistics under standard terms. The pronounced cost volatility emphasizes that operational disruptions not only impact service performance but also materially erode profit margins during recovery phases.

Figure 19. Cost per unit (USD) across simulation horizon



A.3. Summary of Scenario A Findings

The simulation provides a structured and quantitative assessment of the sponsor company's vulnerability to localized disruptions at high-risk production sites. Despite proactive redistribution efforts and available inventory buffers, the network demonstrated an inability to fully sustain service levels, demand fulfillment, or revenue protection during the crisis window. Key findings include:

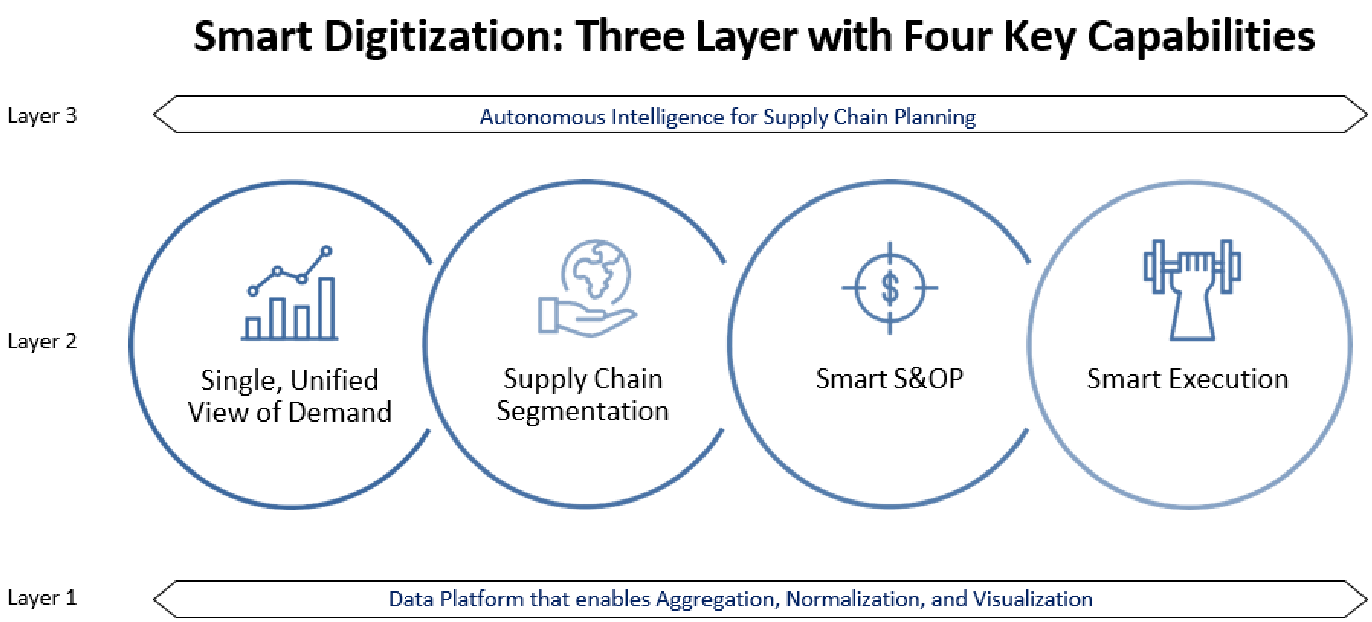
- Plants with shorter time-to-shutdown (TTS) depleted inventory reserves within weeks following the disruption onset.
- Redistribution strategies partially mitigated the supply shortfall but failed to fully compensate for the Japan facility’s production loss.
- Fill rate and revenue exhibited significant declines, with a gradual but delayed post-crisis recovery.
- Inventory buffers initially protected service continuity but collapsed under extended redistribution stress.
- Market share erosion closely tracked the periods of peak disruption and service degradation.
- Per-unit shipment costs escalated sharply during the crisis response and required several months post-crisis to normalize.

Overall, the simulation results illustrate that pre-existing contingency plans, while beneficial, are insufficient without integrated early risk detection mechanisms and adaptive network reconfiguration capabilities. This reinforces the strategic imperative for predictive political risk monitoring, expanded geographic redundancy across operational nodes, and automated decision-making tools capable of translating early risk forecasts into proactive supply chain actions.

4.2.2. Scenario B: Smart Supply Chain Digitization— Three-Layered Architecture with Four Key Capabilities

Scenario B explores the long-term digital futures of the sponsor company's supply chain, focusing on how different levels of technology adoption and governance shape operational resilience. These scenarios were developed through structured interviews with the company's automation, purchasing, strategic sourcing leaders, and risk management team, who outlined current capabilities, ongoing ERP migrations, and future-state aspirations. Building on these insights, we constructed three differentiated scenarios: B1 illustrates a fragmented and vulnerable future with minimal digital advancement, B2 reflects a reactive, compliance-driven pathway with partial progress, and B3 represents the autonomous, fully integrated, and secure digital supply chain. Each scenario is evaluated across core dimensions such as analytics maturity, inventory efficiency, service levels, and strategic risk exposure. Together, they provide a decision-making lens to prioritize technology investments and organizational readiness in the face of accelerating external disruptions.

Figure 20. Smart Supply Chain Digitization (Adapted from Simchi- Levi, 2025)



Building on Simchi-Levi's Smart Supply Chain Digitization model, Figure 20 (Simchi-Levi, 2025), this study structures the digital transformation roadmap into a three-layered architecture. The framework systematically advances from foundational data security to predictive planning to autonomous decision-making.

1. **Data Platform Layer**

The foundational Data Platform Layer consolidates operational information through ERP integration, data aggregation, normalization, and secure real-time visualization. This layer makes sure that reliable data moves smoothly between supply chain functions, which is essential for planning and automating decisions later.

2. Smart Planning Layer

Building on the integrated data foundation, the Smart Planning Layer activates intelligent planning capabilities. It includes creating a single, clear picture of unified demand that captures total demand, using supply chain segmentation strategies, putting smart S&OP (Sales and Operations Planning) into action, enabling smart execution, and building resilience into the system. These capabilities transform static supply chains into dynamic, event-driven systems capable of adaptive responses to internal and external disruptions.

3. Autonomous Intelligence Layer

At the highest level, the Autonomous Intelligence Layer integrates large language models (LLMs), customized machine learning models, and agent-based AI systems to support autonomous decision-making. LLMs and NLP techniques continuously monitor external signals (e.g., geopolitical, supplier, and macroeconomic data), while tailored ML algorithms optimize planning and forecasting. Agentic systems coordinate execution workflows and scenario planning without requiring manual intervention, enabling real-time, adaptive supply chain responses.

Scenario B1: Fractured and Vulnerable Supply Chain (Base approach to Outlook to 2030)

By 2030, the organization fails to achieve meaningful digital transformation across its supply chain systems. Fragmentation persists, with three disconnected ERP platforms operating independently, preventing real-time data aggregation, normalization, or visualization. No comprehensive migration to the cloud-based SAP S/4HANA is completed, and cybersecurity measures are minimal and reactive. Data inconsistencies across platforms are frequent, manual interventions dominate operational workflows, and system vulnerabilities expose the organization to significant cyber risks (SAP, 2023; Deloitte, 2021).

Planning functions remain highly manual and fragmented. A single, unified view of demand is absent, and supply chain segmentation strategies are not implemented. S&OP processes are conducted through spreadsheet-based methods, with reliance on email threads and informal communications for coordination. Exception management is ad hoc, and execution processes are reactive rather than predictive or dynamic. No formal mechanisms exist to update planning parameters based on real-time events or changing supply conditions (Simchi-Levi and Timmermans, 2023).

Autonomous intelligence is absent. No NLP-based external risk sensing systems are deployed, and no AI-driven scenario generation capabilities are in place. Risk identification relies solely on external resources, periodic manual reviews, and anecdotal supplier feedback. The lack of AI adoption limits the organization's ability to anticipate disruptions, model future operational risks, or adjust strategies dynamically.

The organization operates at the descriptive analytic maturity level. Historical data is collected but is used primarily for backward-looking reporting, with little integration into forward-looking planning models. Predictive analytics capabilities are absent, and decision-making remains slow, fragmented, and vulnerable to errors.

Operational outcomes deteriorate. Inventory levels remain elevated, as static buffer policies are maintained to hedge against planning uncertainty, tying up working capital and limiting supply chain responsiveness. Service levels fluctuate inconsistently across regions due to visibility gaps, limited capacity, supplier failures, and planning inaccuracies. The Project.C initiative is unable to scale beyond limited pilot phases, as end-to-end automation and digital integration prerequisites are unmet, stalling production expansion for personalized therapies.

Strategic vulnerabilities intensify. Without integrated digital platforms or embedded cybersecurity protocols, the organization remains exposed to regulatory non-compliance risks, supplier fraud, and cyberattacks. Fragmented governance and lack of cross-functional alignment inhibit corrective actions, entrenching inefficiencies and increasing operational fragility over time. Competitive disadvantage widens as digitally mature rivals achieve market growth, faster innovation, higher agility, and stronger customer trust.

Scenario B2: Reactive, Compliance-Driven Future (Middle approach to Outlook to 2030)

By 2030, the organization achieves partial progress toward digital transformation, driven primarily by external regulatory requirements rather than internal strategic initiatives. Two of the three legacy ERP systems are partially integrated under on-premises SAP S/4HANA, but persistent gaps in system consolidation, master data governance, and cybersecurity architecture remain. While we have improved data aggregation and visualization compared to the baseline, we have not fully normalized or secured across all operational domains. Cybersecurity protocols are implemented selectively to meet audit requirements but are not embedded systematically into planning and execution processes (SAP, 2023; Deloitte, 2021).

At the planning level, partial smart capabilities are operational. Isolated product categories achieve unified demand visibility, while regions apply segmentation strategies inconsistently. Smart S&OP processes are piloted within select business units, but manual overrides and exception handling continue to dominate enterprise-wide planning activities. Real-time event monitoring and dynamic execution agility are introduced in limited functions but are not standardized across the organization (Simchi-Levi and Timmermans, 2023).

Autonomous intelligence is adopted experimentally. NLP-based external risk sensing tools are piloted in supplier risk management and limited forecasting applications, but these systems are siloed and not fully integrated into core planning workflows. Scenario generation remains manual, relying on periodic reviews rather than continuous AI-driven adaptations. The absence of a unified governance framework for AI adoption limits scalability and organizational learning from pilot implementations.

The organization operates at the predictive analytic maturity level. Data-driven forecasting models and supplier analytics are utilized within specific functional areas but are not connected to end-to-end supply chain planning. Predictive insights are generated, but decision execution remains delayed by manual interventions and fragmented systems.

Operational outcomes reflect a hybrid state. Inventory levels are moderately optimized through predictive demand sensing in piloted segments, but company-wide buffers remain elevated to compensate for planning uncertainties. Service levels improve modestly, primarily in regions where pilot projects succeed, but systemic agility remains constrained. The Project.C initiative progresses but faces delays in scaling due to incomplete system integration, isolated automation islands, and uneven data quality across manufacturing and supply nodes.

Strategic risks persist. Despite achieving basic cybersecurity and planning automation standards to meet compliance audits, fragmented governance and inconsistent planning discipline continue to expose systemic vulnerabilities. Without comprehensive data platform consolidation and enterprise-wide AI integration, the organization remains vulnerable to regulatory shifts, cyberattacks, and competitive disruptions.

Scenario B3: A Secure and Connected Future (Best approach to Outlook to 2030)

By 2030, the organization completes a full migration to SAP S/4HANA, consolidating fragmented ERP systems into a unified, secure data platform. Migration utilizes all core features of S/4HANA, including real-time analytics, cloud-native deployment, and advanced modules for planning, warehouse management, and transportation orchestration. This platform is extended via the SAP Business Technology Platform (BTP), enabling modular integration of IoT data, machine learning models, and API-based extensions. Aggregation, normalization, and visualization processes are fully automated, ensuring consistent, real-time operational visibility across supply chain domains. Cybersecurity protocols aligned with ISO 27001 and the NIST Cybersecurity Framework are embedded into infrastructure, including anomaly detection, encryption standards, and role-based access control (SAP, 2023; IBM, 2023).

On this foundation, intelligent planning capabilities are fully operational. A single, unified view of demand enables synchronized planning across products, regions, and functions. Supply chain segmentation strategies are dynamically applied and regularly recalibrated. Smart S&OP processes are continuously updated based on real-time inputs. Exception management is handled autonomously, with minimal need for manual overrides. Predictive models monitor demand shifts, supply disruptions, and capacity constraints, allowing planners to operate with event-driven precision.

At the autonomous intelligence level, a full AI stack is embedded across planning and execution. Generative AI models support scenario simulation and narrative synthesis; customized machine learning models provide high-resolution forecasting, segmentation, and anomaly detection; and agent-based AI systems autonomously coordinate planning decisions and execution tasks. NLP tools continuously monitor external data streams—news, regulatory updates, and supplier signals—to detect emerging risks. Agentic AI enables system-wide adjustments based on this intelligence without requiring manual recalibration. These combined capabilities support real-time scenario generation, self-adjusting strategy recommendations, and workflow automation.

The organization operates at an autonomous analytics maturity level, characterized by real-time learning, adaptive decision-making, and decentralized execution. Predictive demand sensing replaces static inventory rules, reducing inventory costs by 15–30% and improving service levels by 20–40%. Inventory buffers are dynamically allocated based on projected demand volatility and supply risk exposure, not historical averages. Strategic planning cycles shift from quarterly reviews to continuous, AI-driven optimization loops.

Operational risks, including cyber threats, demand shocks, and supplier volatility, are mitigated proactively through system-wide monitoring and autonomous response mechanisms. The Project.C personalized therapy initiative achieves full scalability, driven by modular manufacturing systems, digital process control, and end-to-end integration. Batch traceability, quality monitoring, and scheduling are executed by AI agents with real-time feedback loops.

The company demonstrates structural resilience, operational agility, and strategic foresight. It is positioned not just to withstand disruption but to thrive in uncertainty. By embedding autonomous AI capabilities across its supply chain, the organization unlocks a step-change in responsiveness, efficiency, and innovation.

4.2.4. Scenario Evaluation and Comparative Analysis

To systematically assess the strategic implications of the three scenarios, a structured evaluation is conducted across six core dimensions in Table 2. These dimensions are based on the Smart Supply Chain Digitization framework and include data platform activation, smart planning activation, autonomous intelligence activation, analytics maturity level, operational outcomes, and strategic risks. This structured comparison provides a consistent lens to measure how various levels of digital maturity impact supply chain resilience, agility, and vulnerability.

Table 2. Scenario Evaluation and Comparative Analysis

Dimension	**Scenario B1: Fractured and Vulnerable Supply Chain**	**Scenario B2: Reactive Compliance-Driven Future**	**Scenario B3: Secure and Connected Future**
Data Platform Activation	Fragmented legacy ERP systems, no cloud deployment, significant cybersecurity gaps	Partial on-premises SAP S/4HANA migration, selective cloud use, cybersecurity implemented to satisfy audits	Full cloud-based SAP S/4HANA migration, cloud-native capabilities, BTP integration, full cybersecurity embedded
Smart Planning Activation	Manual spreadsheet-based planning, no segmentation, reactive execution	Partial deployment of smart S&OP pilots, inconsistent segmentation, manual overrides dominate	Fully embedded smart S&OP, segmentation, dynamic execution, and resilience
Intelligence Activation	No AI or generative systems, manual risk monitoring only	Experimental AI pilots in isolated functions, no enterprise-wide integration	Fully embedded autonomous AI models and NLP-driven risk sensing

Analytics Maturity Level	Descriptive Analytics (historical reporting only)	Predictive Analytics (limited forecasting, partial risk sensing)	Autonomous Analytics (real-time adaptive planning)
Operational Outcomes	Elevated inventory buffers, volatile service levels, Project.C scaling stalled	Modest inventory and service improvements in pilot areas, delayed Project.C scaling	15–30% inventory reduction, 20–40% service level improvement, full Project.C scalability
Strategic Risks Remaining	High risks (cyberattacks, operational failures, regulatory non-compliance, competitive erosion)	Moderate risks (fragmented governance, delayed disruption response)	Minor risks (AI model retraining, evolving cyber threats, continuously mitigated)

The evaluation highlights that Scenario B1 reflects the persistence of fragmented systems and manual processes, resulting in descriptive analytics maturity and substantial operational and cybersecurity risks. Scenario B2 shows partial progress, marked by predictive analytic maturity and selective technological deployment, but continues to suffer from structural fragmentation. Scenario B3 achieves the highest level of supply chain resilience and digital maturity, driven by full activation of foundational, planning, and autonomous layers. The comparative results emphasize the strategic importance of comprehensive digital integration and intelligent planning activation.

4.2.5. Quick Scenario Ranking Overview

To further simplify interpretation, the final scenario outcomes are summarized through an overall ranking based on resilience, risk exposure, and achieved analytics maturity. This quick comparison in Table 3 highlights the relative strategic positioning of each scenario without extensive technical detail.

Table 3. Scenario Ranking

Scenario	Resilience	Risk Exposure	Digital Maturity
B1	Low	High	Descriptive
B2	Moderate	Medium	Predictive
B3	High	Low	Autonomous

The ranking confirms that Scenario B1 exposes the organization to persistent risks and competitive disadvantages, driven by insufficient technological advancement and weak operational governance. Scenario B2 represents a constrained trajectory where some operational improvements are realized but systemic vulnerabilities remain. Scenario B3 positions the organization for superior agility, risk management, and future growth through full digital enablement.

4.2.6. Summary of Scenario B Findings

The comparative scenario evaluation clearly demonstrates that full digital integration, intelligent planning activation, and autonomous decision-making capabilities are essential for achieving future supply chain resilience, agility, and competitiveness. Based on the insights gained from the scenario analysis, the following strategic actions are recommended to transition the organization toward the Secure and Connected Future.

First, the organization must complete the full integration of its ERP landscape under SAP S/4HANA, ensuring that cloud-native capabilities, real-time analytics, and the SAP Business Technology Platform (BTP) modular extensions are fully leveraged. Data aggregation, normalization, and secure visualization must be operationalized across all operational domains, with embedded cybersecurity frameworks aligned with ISO 27001 and NIST standards. Consolidating data platforms is foundational to achieving trusted, real-time visibility necessary for dynamic supply chain orchestration.

Second, the company should institutionalize the Smart Planning Layer by embedding intelligent planning capabilities across functions and regions. A single, unified view of demand must be achieved at the enterprise level, supported by systematic supply chain segmentation and dynamic smart S&OP execution. Real-time exception management must replace manual interventions, and operational resiliency must be structured as a core system feature rather than an ad hoc reaction to disruptions. Planning processes must shift from static cycles to adaptive, event-driven responses aligned with real-time market signals.

Third, the organization should deploy and scale autonomous intelligence across planning and execution workflows. Large language models (LLMs) and natural language processing (NLP) techniques should be integrated to automate scenario generation, external risk sensing, and strategic adjustment recommendations. Autonomous AI systems must be embedded not as isolated pilots but as enterprise-wide operational enablers, supported by dedicated governance structures to ensure accountability, reliability, and ethical use.

Fourth, the planning and risk management approach must shift from forecast-driven models to consumption-driven, real-time adaptive systems. Predictive demand-sensing models must replace static inventory buffers, enabling significant reductions in working capital requirements while simultaneously improving service levels. Supply chain decisions should be based on live demand signals, dynamic risk assessments, and AI-generated scenario simulations, not on historical averages or manual judgment.

Finally, the company must establish a permanent cross-functional governance body responsible for digital transformation leadership, cybersecurity oversight, and continuous process innovation. This capability team should drive system adherence, oversee master data quality, monitor real-time cybersecurity threats, and ensure continuous improvement of planning, execution, and risk monitoring processes.

Collectively, these strategic actions provide a clear, actionable pathway for transitioning from fragmented legacy systems toward an integrated, autonomous, and resilient supply chain architecture. They enable not only the successful scaling of initiatives like Project.C but also position the organization for sustained competitive advantage in an increasingly uncertain and digitized operating environment.

4.3. Limitation of The Project

A key limitation of this study was the inability to access the actual planning parameters and internal operational and risk data from the sponsor company due to confidentiality constraints. As a result, several assumptions were made to simulate supply chain parameters, such as inventory levels, production capacity, time-to-survive, and recovery times. While stakeholder interviews helped guide some of these assumptions, the absence of real-time transactional data limited the accuracy of scenario calibration and model validation. Consequently, the outcomes of Scenario A and Scenario B should be interpreted as indicative rather than definitive, and future work should include access to granular internal data to enhance model simulation outcomes.

5. CONCLUSION

This research was motivated by the increasing frequency and complexity of global disruptions that challenge the resilience of advanced supply chains, particularly in the personalized medicine sector. Traditional risk management approaches often fail to anticipate long-term threats or translate early warning signals into actionable strategies. To address this gap, the project developed a forward-looking framework that integrates Natural Language Processing (NLP), machine learning, and scenario planning to detect emerging risks and simulate their operational impact. The purpose was to provide supply chain leaders with a practical, data-driven approach to stress-test future scenarios and inform strategic decisions on digital transformation, resilience planning, and risk governance.

5.1. Management Recommendations

This research highlights that proactive, data-driven, and technology-enabled risk management frameworks are no longer optional but imperative for supply chains operating in high-uncertainty sectors like cell therapy. To sustain competitiveness and resilience over the long term, companies must move beyond reactive risk management models and instead embed predictive and autonomous technologies into core planning and execution processes.

The study recommends that the sponsor company prioritize full ERP platform integration under SAP S/4HANA, supported by real-time cybersecurity frameworks, to achieve trust and seamless operational visibility. Intelligent planning capabilities should be embedded through consumption-driven S&OP, dynamic segmentation, and real-time event monitoring. Furthermore, the organization must institutionalize the use of autonomous intelligence, including NLP-driven risk sensing and AI-based scenario generation, to continuously anticipate disruptions and proactively adjust operational strategies. Establishing a permanent, cross-functional digital governance body is critical to sustaining digital maturity, maintaining cybersecurity vigilance, and driving continuous operational innovation.

5.2. Future Work

To maintain the framework proposed, we recommend establishing an annual update cycle for external risk factors. This can be done by re-querying global news database and published political, economic, and security risk indices. Internally, operational parameters such as facility locations, critical supplier and material lists or any changes in the company's network should be fed into the system to ensure that the model remains relevant. For continuous improvement, data ingestion and model retraining should be automated in integrated pipelines. Over time, incorporating feedback loops from decision-makers and outcomes from past scenarios can further enhance the accuracy of the model.

While this study provides a foundation for integrating NLP-enhanced scenario planning into long-term risk management, several areas warrant future research. First, future work should explore integrating real-time operational data, such as IoT-based factory performance and transportation telemetry, into the risk prediction models to improve responsiveness and granularity. Second, further advancements in explainable AI (XAI) methods could enhance the interpretability and trustworthiness of autonomous scenario models deployed in supply chain operations. Third, conducting longitudinal studies that evaluate the financial impact and operational outcomes of predictive and autonomous models in live environments would strengthen the business case for full-scale adoption. Lastly, collaborative research across different therapeutic modalities and manufacturing settings could validate the broader applicability of the proposed framework beyond cell therapy.

5.3. Contribution

This capstone presents a next-generation risk management framework that combines scenario planning and natural language processing to proactively forecast, simulate, and mitigate long-term supply chain risks. By demonstrating how dynamic political, economic, and operational factors can be monitored and translated into actionable strategic decisions, the study offers a practical model for organizations seeking to strengthen their resilience in uncertain environments. The integration of smart digitalization layers— data platform activation, smart planning, and autonomous intelligence— enables a structured pathway toward predictive and autonomous supply chain decision-making. Scenario analysis reinforces that early adoption of these capabilities can reduce operational risks, lower costs, and enhance service performance. This work contributes to advancing the digital transformation of supply chain risk management, establishing a robust blueprint for navigating future uncertainties in personalized medicine and beyond.

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