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Transforming supply chain resilience: Frameworks and advancements in predictive analytics and data-driven strategies

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Abstract

Supply chain resilience is critical in maintaining operational stability and competitive advantage in an increasingly volatile global economy. This paper explores the transformative potential of predictive analytics and data-driven strategies in enhancing supply chain resilience. Organizations can achieve real-time monitoring, improved demand forecasting, and robust risk assessment capabilities by integrating advanced technologies such as IoT, big data, and cloud computing. These innovations enable proactive decision-making, agility, and recovery from disruptions across supply chain stages, including procurement, production, and distribution. The paper also discusses frameworks and models for leveraging predictive analytics, highlighting their application in mitigating risks and optimizing operations. Furthermore, it addresses challenges such as data quality, technological complexity, and cybersecurity, providing actionable recommendations for organizations seeking to implement these tools. The findings underscore the importance of data-driven approaches in building resilient supply chains equipped to navigate uncertainties and maintain efficiency in a rapidly evolving market.

Keywords: Supply chain resilience; Predictive analytics; Data-driven strategies; IoT in supply chains; Risk assessment; Demand forecasting

1. Introduction

In an increasingly interconnected and volatile global economy, supply chain resilience has emerged as a critical priority for organizations. Supply chain resilience refers to the ability of a supply chain to anticipate, absorb, and recover from disruptions while maintaining continuous operations and adapting to future uncertainties (Ibrahim, Centeno, Patterson, & Callahan, 2021). This capability is essential in light of challenges such as global pandemics, geopolitical tensions, natural disasters, and cyberattacks, which can cause significant disruptions to supply chain networks. Resilient supply chains mitigate risks and provide organizations with a competitive advantage by ensuring reliability, agility, and customer satisfaction even in times of crisis (Lund, DC, & Manyika, 2020).

The importance of supply chain resilience extends beyond individual organizations, influencing global economic stability. Disruptions in one segment of a supply chain can ripple across industries, causing economic losses, resource shortages, and operational delays (Herold & Marzantowicz, 2023). For example, the COVID-19 pandemic revealed vulnerabilities in global supply chains, such as dependency on single-source suppliers and limited visibility into the extended supply network. These vulnerabilities underscored the need for businesses to build adaptive systems capable of responding swiftly to disruptions (Ivanov, Dolgui, & Sokolov, 2019).

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Predictive analytics and data-driven strategies play a transformative role in strengthening supply chain resilience. Predictive analytics involves the use of statistical techniques, machine learning algorithms, and data models to forecast future outcomes based on historical and real-time data. This capability enables organizations to anticipate potential disruptions, optimize inventory levels, and proactively address risks before they materialize (Adewusi et al., 2024). For example, by analyzing weather patterns and geopolitical data, predictive analytics can identify potential risks to shipping routes or production facilities, allowing companies to adjust their operations in advance (Kalusivalingam, Sharma, Patel, & Singh, 2022).

Data-driven strategies further enhance supply chain resilience by leveraging vast amounts of information to inform decision-making processes. These strategies encompass real-time monitoring, scenario planning, and performance tracking, enabling businesses to respond dynamically to changing conditions. For instance, data collected through Internet of Things (IoT) devices can provide insights into equipment performance, ensuring timely maintenance and reducing the likelihood of unexpected breakdowns. Similarly, integrating data from suppliers, distributors, and customers enhances supply chain visibility, fostering collaboration and minimizing uncertainties (Ikevuje, Anaba, & Iheanyichukwu, 2024).

This paper aims to explore frameworks and recent advancements that enable resilient and agile supply chains through predictive analytics and data-driven strategies. The discussion will cover key components of supply chain resilience, frameworks that incorporate data-driven approaches, and advancements in predictive analytics technologies. By examining these aspects, the paper aims to comprehensively understand how organizations can leverage innovative tools to build robust supply chains that can withstand disruptions and thrive in a complex, rapidly changing environment. The exploration of this topic is timely, as businesses increasingly recognize the strategic value of resilience in achieving long-term success. While traditional supply chain management practices often focus on cost efficiency and lean operations, these approaches can leave organizations vulnerable to unexpected events. Emphasizing resilience shifts the focus to adaptability and risk mitigation, which are essential for navigating the uncertainties of today's global marketplace.

2. Supply Chain Resilience

2.1. Supply chain resilience and its key components

Supply chain resilience is the ability of a supply chain to withstand and recover from disruptions, adapting to new circumstances and returning to optimal performance levels. In the face of unprecedented global challenges, including pandemics, political instability, and climate-related disruptions, resilience has become crucial for ensuring the sustainability and competitiveness of businesses (Pettit, Croxton, & Fiksel, 2019). Traditional supply chain management approaches focused on lean operations and cost efficiency, often leaving supply chains vulnerable to unforeseen events. In contrast, a resilient supply chain can quickly anticipate disruptions, respond to them, and minimize their impact on operations and stakeholders (Katsaliaki, Galetsi, & Kumar, 2022).

The key components of supply chain resilience include adaptability, responsiveness, and recovery. Adaptability refers to the ability of the supply chain to change in response to shifts in market demand, resource availability, or operational constraints. This adaptability is vital when disruptions such as natural disasters or geopolitical events create sudden changes in supply or demand. For example, a company that relies on a single supplier for a critical component is at risk if that supplier encounters difficulties. By diversifying suppliers or developing flexible production processes, a resilient supply chain can quickly adjust to new sources of supply or alternate production methods (Kazancoglu, Ozbiltekin-Pala, Mangla, Kazancoglu, & Jabeen, 2022).

Responsiveness is another essential component, defined as the ability of the supply chain to detect and react to changes rapidly. Responsive supply chains utilize real-time data and communication to sense disruptions early and make adjustments as needed. For instance, during the COVID-19 pandemic, companies with responsive supply chains were able to shift production lines or reroute shipments to accommodate lockdowns and new safety protocols. Responsiveness requires close collaboration among suppliers, distributors, and partners to ensure that information flows seamlessly and enables swift decision-making (Novak, Wu, & Dooley, 2021).

Recovery is the capacity of a supply chain to resume normal operations after a disruption has been resolved. This includes restoring production levels, replenishing inventory, and re-establishing logistics routes. A strong recovery capability is essential for minimizing downtime and preventing revenue losses (Thekkoote, 2022). For example, a food retailer that experiences supply disruptions due to a natural disaster may leverage recovery strategies such as redirecting inventory from unaffected areas or negotiating with alternative suppliers to replenish stock quickly.

Recovery-focused strategies are particularly valuable in industries where downtime can lead to significant financial and reputational damage (Handfield, Finkenstadt, Schneller, Godfrey, & Guinto, 2020).

2.2. Major challenges impacting supply chain stability

Despite its importance, achieving supply chain resilience is challenging due to a variety of factors. Major challenges that impact supply chain stability include disruptions, demand fluctuations, and supplier risk. Disruptions can arise from many sources, such as extreme weather events, cyberattacks, and labor strikes. These disruptions can halt production, delay shipments, and compromise product quality, posing a serious risk to businesses and consumers alike. Moreover, global supply chains are often interconnected, meaning that a disruption in one part of the world can quickly affect other regions (Zhu, Chou, & Tsai, 2020).

Demand fluctuations are another challenge, as shifts in consumer behavior or market conditions can lead to unexpected changes in demand. For example, during holiday seasons or promotional events, a sudden spike in demand can strain a company's supply chain, leading to inventory shortages or delays in delivery. Conversely, a decrease in demand can result in excess inventory, which incurs storage costs and reduces profitability. Balancing supply and demand is particularly challenging in industries with high demand variability, such as fashion, electronics, and food and beverage (Adegbola, Adegbola, Amajuoyi, Benjamin, & Adeusi, 2024).

Supplier risk is a critical factor influencing supply chain resilience. Many businesses rely on a limited number of suppliers for key components or raw materials, making them vulnerable to supplier failures. Supplier risk can result from financial instability, capacity limitations, or non-compliance with regulations. Suppose a supplier is unable to meet its obligations. In that case, the entire supply chain may be affected, leading to delays and increased costs. Resilient supply chains often involve multi-sourcing strategies, strategic partnerships, and supplier performance assessments to mitigate supplier risk (Um & Han, 2021).

Data analytics and predictive models are instrumental in addressing these challenges, providing organizations with insights that enhance decision-making and resilience. By harnessing the power of data, companies can gain a deeper understanding of their supply chains and develop proactive strategies to address potential risks (George, 2023). Predictive analytics, in particular, allows businesses to anticipate disruptions by identifying patterns and trends in historical and real-time data. For instance, machine learning algorithms can analyze historical data on demand patterns, supplier performance, and environmental conditions to predict potential risks and optimize inventory levels accordingly (Adewusi et al., 2024).

Predictive models are also valuable for demand forecasting, helping companies to adjust production and inventory levels based on anticipated demand changes. For example, predictive algorithms can consider variables such as seasonal trends, promotional activities, and market conditions to forecast demand accurately. This enables businesses to align production schedules and inventory levels with expected demand, minimizing the risk of stockouts or excess inventory. Moreover, predictive models can identify correlations between different factors, such as weather conditions and consumer purchasing patterns, enabling companies to make data-informed decisions that improve their resilience (Punia & Shankar, 2022).

Supplier risk can also be mitigated through data analytics, as companies can use data to evaluate supplier performance, assess risk factors, and make more informed sourcing decisions. For instance, data analytics platforms can monitor supplier reliability, quality control, and compliance with regulations, allowing businesses to identify potential risks and take action before they affect operations. By using predictive models to assess supplier stability and reliability, companies can develop contingency plans, diversify their supplier base, or establish backup suppliers to ensure a continuous supply of critical materials (Adebayo, Paul, & Eyo-Udo, 2024).

In addition, real-time monitoring enabled by data analytics improves supply chain responsiveness by providing instant insights into operational status. For example, the Internet of Things (IoT) allows companies to monitor inventory levels, equipment conditions, and transportation progress in real-time. These insights enable companies to detect potential issues, such as equipment malfunctions or shipping delays, and respond immediately. Real-time data also enhances collaboration among supply chain partners, as stakeholders can access shared data and effectively coordinate responses to disruptions (Oliveira & Handfield, 2019).

3. Frameworks for Data-Driven Supply Chain Resilience

3.1. Various frameworks used in building resilient supply chains

Building resilient supply chains is a strategic imperative in today's rapidly evolving global environment. Frameworks for data-driven supply chain resilience have emerged as powerful tools that integrate data, analytics, and decision-making to help organizations withstand and adapt to disruptions (Bechtsis, Tsolakis, Iakovou, & Vlachos, 2022). These frameworks enable companies to harness predictive analytics, machine learning, and artificial intelligence (AI) to forecast potential risks and optimize operations. By providing structured methodologies to enhance resilience, these frameworks help companies minimize downtime, reduce costs, and maintain operational stability. Key frameworks focus on integrating data across supply chain stages, utilizing analytics for insightful predictions, and fostering agile decision-making processes.

One critical aspect of resilient supply chain frameworks is data integration. Data integration involves combining data from various sources across the supply chain to create a unified view of operations. Many organizations operate in silos, with data residing separately in procurement, production, and distribution. Such fragmentation limits visibility and hinders collaboration, making it challenging to respond effectively to disruptions (Bechtsis et al., 2022). By integrating data from suppliers, manufacturing sites, and distribution centers, companies gain a holistic view of their operations, allowing for real-time insights and improved decision-making. For example, cloud-based platforms that aggregate data from Internet of Things (IoT) sensors, enterprise resource planning (ERP) systems, and supplier networks enable seamless data sharing across departments and facilitate quicker responses to unexpected events.

Another key component of these frameworks is analytics. Analytics tools enable organizations to process vast amounts of data and extract meaningful insights. Descriptive analytics provides a historical view, helping companies understand past trends and patterns, while diagnostic analytics identifies the underlying causes of disruptions (Osman, 2019). Predictive analytics, however, plays an especially vital role in resilience frameworks. By analyzing historical data alongside real-time inputs, predictive analytics generates forecasts and identifies patterns that signal potential risks. For instance, by examining weather data, transportation logs, and supplier performance records, predictive models can anticipate shipment delays or equipment failures, enabling proactive measures to avoid operational disruptions (Mohamed, Najafabadi, Wah, Zaman, & Maskat, 2020).

Effective decision-making processes are fundamental to resilient supply chain frameworks. Data-driven decision-making leverages analytics to guide strategies, aligning decisions with real-time data to enhance responsiveness. Prescriptive analytics, a subset of decision-making tools, recommends specific actions based on predictive insights, allowing companies to select the optimal course of action in a given scenario. In a disruption, for example, prescriptive analytics can suggest alternative suppliers, recommend inventory redistribution, or adjust production schedules. This data-driven decision-making approach improves agility, providing supply chain managers with actionable insights that empower swift, well-informed responses to dynamic conditions (Hassan & Mhmood, 2021).

3.2. Models and strategies to anticipate and mitigate risks

Several models and strategies within these frameworks leverage predictive analytics, machine learning, and AI to anticipate and mitigate risks. For instance, the Control Tower model uses advanced analytics to provide centralized, real-time visibility across the entire supply chain. By consolidating data from all supply chain stages, a Control Tower can identify disruptions as they occur and suggest corrective actions, such as rerouting shipments or adjusting production volumes (Qolomany et al., 2019). Machine learning algorithms continuously analyze data, learning from historical disruptions to improve prediction accuracy and resilience over time. The Control Tower model exemplifies how predictive analytics can drive proactive risk management by identifying potential bottlenecks and suggesting alternative courses of action (Kabashkin, 2024).

Another prominent model is the Digital Twin, which uses AI and machine learning to create a virtual replica of the physical supply chain. Digital Twins simulate various supply chain scenarios, enabling organizations to predict how different disruptions will impact operations. By running simulations, companies can test different responses, identifying which actions will most effectively restore normalcy in the face of specific disruptions (Alexopoulos, Nikolakis, & Chryssolouris, 2020). For example, a Digital Twin can simulate the impact of a supplier failure, providing insights into how stock levels, production schedules, and delivery timelines will be affected. This ability to anticipate and prepare for disruptions makes Digital Twins an invaluable tool for enhancing supply chain resilience.

Supply chain resilience frameworks are applicable across multiple stages, from procurement to production and distribution. In procurement, data-driven frameworks support supplier risk assessment and diversification strategies. Predictive analytics models can evaluate supplier reliability by examining historical performance, financial stability, and compliance records, identifying suppliers that pose potential risks (Cavalcante, Frazzon, Forcellini, & Ivanov, 2019). With this information, companies can diversify suppliers or develop contingency plans, reducing dependency on high-risk suppliers. For instance, a predictive model might indicate that a supplier's location is prone to weather-related disruptions, prompting the organization to find alternative sources in more stable regions (Liang, Zhu, Lee, Cheng, & Yeung, 2024).

Machine learning algorithms can optimize manufacturing processes in the production stage by analyzing real-time data from equipment, inventory levels, and demand forecasts. Predictive maintenance, a key application of machine learning, uses data from IoT sensors to monitor machinery conditions and predict equipment failures. By detecting anomalies in equipment performance, predictive maintenance allows companies to schedule repairs proactively, preventing unplanned downtime and ensuring uninterrupted production. Moreover, data-driven frameworks in production can adjust manufacturing output in response to changing demand levels, minimizing excess inventory and reducing waste (Jeyaraman, Krishnamoorthy, Kumar Konidena, Ranjan, & Sistla, 2024).

In the distribution stage, AI-powered frameworks can optimize logistics by analyzing variables such as shipping routes, fuel costs, and delivery timelines. Route optimization algorithms, for instance, can identify the most efficient delivery paths, reducing transportation costs and improving delivery speed. Additionally, predictive analytics can help companies anticipate potential disruptions in transportation, such as port congestion or traffic delays, and adjust routes accordingly. This optimization level enhances the resilience of distribution networks by ensuring that products reach their destinations on time, even in the face of logistical challenges (Dhaliwal, 2022).

4. Advancements in Predictive Analytics for Supply Chains

4.1. Real-Time Monitoring

Real-time monitoring has become essential for resilient supply chain management, offering businesses up-to-the-minute insights into various aspects of their operations. Companies can track shipments, monitor equipment performance, and observe market conditions through real-time monitoring. IoT plays a significant role in enabling this monitoring, as IoT devices equipped with sensors can continuously collect and transmit data across the supply chain (Mathews). For instance, in logistics, IoT sensors embedded in vehicles provide real-time information on location, temperature, and humidity, helping ensure that goods arrive on time and in optimal condition. In manufacturing, IoT-enabled sensors can monitor machinery and alert managers to potential issues before they escalate into costly disruptions (Oliveira & Handfield, 2019).

Real-time monitoring also aids in maintaining product quality and compliance. For industries like pharmaceuticals and food, where precise temperature and humidity levels are critical, IoT sensors track environmental conditions and notify managers of any deviations that could compromise product integrity. The ability to take swift action based on real-time insights significantly enhances supply chain resilience by minimizing disruptions and preserving customer trust (Sharma, Bhargava, & Singhal, 2020).

4.2. Demand Forecasting

Demand forecasting is another crucial area where predictive analytics has made significant strides, offering businesses more accurate and adaptable methods for anticipating market demands. Traditionally, demand forecasting relied heavily on historical sales data and static models, which often failed to capture rapid shifts in consumer behavior or account for unforeseen events. Recent advancements in predictive analytics have transformed demand forecasting by integrating real-time data from multiple sources, including social media, market trends, and economic indicators. This integration allows for a more dynamic, comprehensive understanding of demand patterns.

Machine learning and artificial intelligence have significantly improved demand forecasting accuracy by enabling predictive models to learn from new data and adjust forecasts accordingly. For example, during the COVID-19 pandemic, many companies leveraged machine learning to forecast demand amidst highly volatile conditions, helping them adapt inventory levels and prevent stockouts. By refining these models with current data, companies can make proactive decisions to meet customer needs while minimizing excess inventory costs. In this way, advanced demand forecasting enhances supply chain agility and resilience, as companies can adapt more quickly to demand fluctuations (Seyedan & Mafakheri, 2020).

4.3. Risk Assessment and Management

Risk assessment and management are critical components of predictive analytics for resilient supply chains. As supply chains become more global and interconnected, risks increase, ranging from supplier failure to natural disasters to cybersecurity threats. Recent advancements in predictive analytics enable companies to assess and manage these risks with unprecedented precision. By analyzing historical data and identifying risk indicators, predictive models can assess potential vulnerabilities and estimate the likelihood of disruptions. For instance, supply chain managers can use predictive models to evaluate the financial stability of suppliers, detect geopolitical risks, and forecast environmental impacts on supply routes (Aljohani, 2023).

The application of big data and AI in risk management has proven particularly effective in preempting disruptions. For example, some companies employ AI algorithms to analyze satellite imagery, social media activity, and news feeds, detecting potential disruptions in real time. This data-driven approach allows companies to adjust their strategies preemptively, such as by rerouting shipments or diversifying suppliers. Advanced risk assessment helps prevent losses and provides a strategic advantage by enabling companies to navigate risks proactively (Rane, Paramesha, Choudhary, & Rane, 2024).

4.4. Technologies Enabling Predictive Analytics in Supply Chains

Technologies like IoT, big data, and cloud computing largely drive predictive analytics advancements. IoT devices capture valuable real-time data across the supply chain, from production facilities to distribution centers. By feeding this data into analytics systems, IoT devices create a foundation for predictive insights that enhance supply chain transparency and control. Big data, in turn, allows companies to process and analyze massive datasets to uncover patterns and trends. For example, big data analytics can reveal correlations between weather patterns and transportation delays, helping companies adjust their logistics strategies accordingly (Paramesha, Rane, & Rane, 2024).

Cloud computing has also facilitated these advancements by providing scalable data storage and analysis infrastructure. With cloud-based analytics platforms, companies can process data from various sources in real time and make insights accessible to stakeholders across multiple locations. This centralization of data fosters collaboration and accelerates decision-making. Additionally, cloud computing reduces the need for significant on-site infrastructure, making predictive analytics more accessible and cost-effective for organizations of all sizes (Yilmaz, Demir, Kaplan, & Demirci, 2020).

4.5. Challenges and Limitations of Adopting Advanced Analytics

While the advancements in predictive analytics offer numerous benefits, they also pose challenges for organizations seeking to integrate these tools into their supply chains. One of the primary challenges is data quality. Predictive analytics relies heavily on accurate, high-quality data, yet many organizations struggle with data silos, inconsistent formats, and incomplete records. Poor data quality can lead to unreliable predictions, undermining the effectiveness of analytics-driven strategies. Implementing data governance frameworks and investing in data cleaning processes are crucial steps toward overcoming this challenge, but these efforts require time and resources.

Another significant challenge is technological complexity. Advanced analytics systems, particularly those involving AI and machine learning, require specialized skills to develop, implement, and maintain. Many organizations lack in-house expertise in these areas, which can hinder their ability to leverage predictive analytics fully. Hiring skilled data scientists and analysts, or partnering with external providers, can help address this gap, though it may also increase costs (Dwivedi et al., 2021).

Data security and privacy present additional concerns, especially as supply chains become more interconnected and data flows across multiple stakeholders. Cybersecurity threats, including data breaches and hacking, can compromise sensitive information, disrupt operations, and damage an organization's reputation (Sobb, Turnbull, & Moustafa, 2020). To mitigate these risks, companies must invest in robust cybersecurity measures like encryption, firewalls, and access controls. However, implementing these protections can be complex and may add to operational costs. Lastly, organizational culture and resistance to change can limit the effectiveness of predictive analytics. Many employees may be accustomed to traditional decision-making processes and reluctant to rely on data-driven insights. Overcoming this resistance requires strong leadership and a commitment to fostering a culture that values data-driven decision-making. Training programs and change management initiatives can help employees understand the benefits of predictive analytics, ultimately enhancing buy-in and collaboration (Kolasani, 2023).

5. Conclusion and Recommendations

The transformative role of predictive analytics and data-driven strategies in building resilient supply chains is becoming increasingly evident as companies strive to navigate a complex and volatile global market. Predictive analytics enables organizations to anticipate and adapt to disruptions by providing insights that inform proactive decision-making, enhance operational flexibility, and optimize resource allocation. The integration of real-time monitoring, advanced demand forecasting, and sophisticated risk assessment tools offers supply chain managers the precision and speed needed to react effectively to changing circumstances. Furthermore, the application of technologies like IoT, big data, and cloud computing has amplified the potential of predictive analytics, making it possible to gather, analyze, and utilize vast datasets to foster a comprehensive view of the entire supply chain.

Through these advancements, organizations can achieve improved supply chain visibility and responsiveness, significantly reducing the negative impacts of disruptions. Real-time monitoring, for example, allows companies to track shipments, assess inventory levels, and adjust production rates instantly based on updated information. Demand forecasting, enhanced through machine learning, enables firms to prepare for market fluctuations and consumer behavior shifts, mitigating the risks of overstocking or stockouts. Similarly, predictive risk assessment empowers organizations to identify and manage potential vulnerabilities, from supplier insolvencies to logistical bottlenecks, thus reinforcing their ability to recover quickly from setbacks.

However, organizations must strategically implement these frameworks and technologies to fully harness the potential of predictive analytics. First, companies should prioritize establishing robust data governance practices to ensure data quality, consistency, and accessibility across departments and supply chain partners. Accurate and comprehensive data is foundational for reliable predictive analytics, and efforts should be made to eliminate silos and standardize data formats. This can involve implementing data integration tools that aggregate information from various sources, thus creating a cohesive data environment conducive to predictive modeling.

Second, investing in talent and training is essential for building internal expertise in data analytics, machine learning, and cybersecurity. The complexity of predictive analytics tools requires a skilled workforce capable of managing and interpreting data insights. Organizations can benefit from offering training programs or partnering with external analytics providers to bridge knowledge gaps and gain specialized support. Third, companies should enhance cybersecurity measures to protect sensitive data and reduce the risks associated with increased connectivity across supply chains. As supply chains incorporate IoT devices and cloud-based platforms, vulnerabilities to cyber threats can grow. Strong cybersecurity policies, including data encryption, access controls, and regular security audits, are critical to safeguarding both organizational data and customer information.

Finally, fostering a culture that values data-driven decision-making will enable organizations to overcome internal resistance to new technologies. Encouraging cross-functional collaboration, providing data literacy programs, and showcasing the benefits of predictive analytics can enhance employee engagement and align the organization toward resilience-focused objectives. As supply chain disruptions continue to challenge global commerce, predictive analytics and data-driven frameworks offer invaluable tools for creating more resilient, agile supply chains. Organizations proactively adopting these innovations will be better positioned to navigate future challenges, optimize performance, and maintain a competitive edge in an unpredictable world.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest exists among the Authors.

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