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Integrating human-centric automation and sustainability through the NAToRM framework: A neuromorphic computing approach for resilient industry 5.0 supply chains

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ABSTRACT

Industry 5.0 supply chains face critical challenges in effectively managing the rapidly growing volume, variety, velocity, and veracity of big data while simultaneously ensuring sustainability, privacy, and ethical practices. The complex and interconnected nature of modern supply networks and the swift adoption of advanced technologies have created an urgent need for innovative frameworks to navigate these multifaceted challenges. Existing approaches often fail to adequately address the unique demands of Industry 5.0, lacking the ability to process data in real time, uncover deep insights, and enable dynamic, risk-informed decision-making. Moreover, there is a pressing need for frameworks that emphasize interdisciplinary collaboration and proactively address the potential negative impacts of emerging technologies. This paper introduces a novel, multidisciplinary framework that integrates cutting-edge techniques to tackle these challenges head-on, paving the way for more resilient, intelligent, and adaptable supply chains in the Industry 5.0 era.

1. Introduction

The rapid evolution of technology and science has positioned data as a catalyst for progress across various sectors, including finance, healthcare, meteorology, and social science. This transformation has led to a growing emphasis on harnessing the potential of big data through innovative technologies and methodologies aimed at advancing knowledge and generating significant insights. Big data, characterized by its vast volume, high velocity, wide variety, and veracity, has revolutionized research and technology domains, proving essential in weather forecasting, climate change analysis, artificial intelligence, and cybersecurity (El Hachimi et al., 2022; Hassani & Silva, 2015; Hassani et al., 2019; Kersting & Meyer, 2018; Yang et al., 2019). The emergence of Industry 4.0 marked a significant shift in manufacturing and supply chain management, driven by the integration of advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics (Bag et al., 2020; Dwivedi et al., 2021). This fourth industrial revolution focused on automation, data exchange, and interconnectivity in manufacturing technologies, leading to increased efficiency, flexibility, and productivity. However, as the world moves towards Industry 5.0, a more human-centric approach is adopted, emphasizing the collaboration between humans and machines, sustainability, and resilience (Bednár and Welch, 2019; European Commission, 2021). This transition presents both opportunities and challenges for supply chain management, particularly in the context of big data analytics and technology integration.

Despite the advantages of big data, its management presents notable challenges due to its large size and complex, high-dimensional structures (Šuman, 2020; Ying & Liu, 2021). Traditional statistical methodologies often struggle with big data's nonlinearity and dynamic characteristics, underscoring the need for more sophisticated analytical techniques. While topographic data analysis (TDA), neuromorphic learning, and reinforcement learning (RL) have emerged as crucial tools for thoroughly analyzing and extracting meaningful insights from extensive datasets (Cao, 2019; Karmakar & Mukhopadhyay, 2018; Peñaloza Figueroa & Vargas Perez, 2017; Zhou et al., 2019), the current literature on sustainable and automated supply chain management in Industry 5.0 lacks comprehensive frameworks that address the multifaceted challenges associated with big data analytics, technology integration, and ethical considerations (Ateş et al., 2021; Govindan et al.,

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2020). Existing approaches often fail to adequately address the unique demands of Industry 5.0, lacking the ability to process data in real-time, uncover deep insights, and enable dynamic, risk-informed decision-making.

This study aims to bridge this gap by introducing a holistic framework that integrates neuromorphic computing, persistent homology, spatiotemporal matrices, and reinforcement learning (RL) to address the critical challenges Industry 5.0 supply chains face in managing big data effectively while ensuring sustainability, privacy, and ethical practices. The primary research question guiding this study is: How can integrating neuromorphic computing, persistent homology, spatiotemporal matrices, and reinforcement learning enable resilient, intelligent, and adaptable supply chains in the Industry 5.0 era? We propose the Neuromorphic Adaptive Topological Risk Management (NAToRM) framework to answer this research question. This innovative approach leverages the real-time data processing capabilities of neuromorphic computing (Cao, 2019; Schuman et al., 2022), the novel lens of persistent homology for analyzing high-dimensional data structures (Carlsson, 2009; Zomorodian & Carlsson, 2004), the geographical and temporal insights provided by spatiotemporal matrices, and the adaptive decision-making strategies of RL (Coletti et al., 2020; Karmakar & Mukhopadhyay, 2018; Ren et al., 2022; Zhou et al., 2019). The NAToRM framework aims to ensure data integrity, uphold privacy regulations, and promote stakeholder collaboration, addressing the complexities of data analysis in Industry 5.0 and mitigating the unintended consequences of technology integration in supply chains (Elezaj & Tole, 2018; Noviyanti et al., 2020; Struijs et al., 2014).

The following sections of this paper will provide an in-depth exploration of the critical components that form the foundation of the NAToRM framework. First, a comprehensive literature review will focus on neuromorphic computing, persistent homology, spatiotemporal matrices, and reinforcement learning. This review will establish the current knowledge in these domains and highlight potential synergies and applications relevant to supply chain management in Industry 5.0. Next, a detailed description of the proposed NAToRM framework will be presented, delving into how its components are integrated to create a cohesive and powerful tool for managing the complexities of Industry 5.0 supply chains. The strategic impact of integrating the NAToRM framework within Industry 5.0 supply chains will then be explored, considering its potential to enhance operational efficiency, improve risk management, and foster a more proactive and adaptive approach to supply chain management. Finally, the challenges and future directions associated with implementing the NAToRM framework in real-world settings will be addressed, acknowledging potential obstacles while proposing strategies to overcome them and emphasizing the crucial role of interdisciplinary collaboration. By providing a comprehensive and nuanced exploration of the NAToRM framework, its components, and its potential impact, this paper aims to contribute to the ongoing discourse on the future of supply chain management in the Industry 5.0 era. The insights and perspectives presented herein will serve as a foundation for further research and practical applications, ultimately supporting the development of more resilient, efficient, and socially responsible supply chains in the face of increasingly complex and dynamic global challenges.

2. Literature review: neuromorphic computing: principles, significance, and applications in Industry 5.0 supply chain management

Neuromorphic computing, a rapidly evolving field inspired by the human brain's structure and functionality, offers immense potential for revolutionizing supply chain management in the Industry 5.0 era. By emulating biological neural networks, neuromorphic systems exhibit remarkable energy efficiency, parallel processing capabilities, and suitability for advanced machine learning tasks (Aitsam et al., 2022; Choi et al., 2020; Tang et al., 2019). This approach is particularly relevant for addressing the complex challenges faced by modern supply chains, such as real-time data processing, pattern recognition, and optimization (Abderrahmane et al., 2020; Aimone et al., 2022; Hendy & Merkel, 2022; Park and Kim, 2021). At the core of neuromorphic computing are spiking neural networks (SNNs), which operate on discrete spikes or electrical signals akin to those in biological neurons (Liu et al., 2021; Pritchard et al., 2023; Schuman et al., 2022; Yamazaki et al., 2022). SNNs harness the sparsity and temporal dynamics of biological neural networks, offering a more authentic emulation of brain-like mechanisms and enhancing computational efficiency. Neuromorphic computers exhibit inherent parallelism and scalability, employing event-driven computation that allows neurons and synapses to operate simultaneously (Indiveri et al., 2011; Schuman et al., 2022). The development of neuromorphic computing hardware has witnessed significant advancements in recent years, integrating advanced materials such as memristors and organic electronic materials (Aitsam et al., 2022; S. Choi et al., 2020; Tang et al., 2019; Xiao & Huang, 2016). These materials enable the construction of compact, energy-efficient devices that closely resemble the behavior of biological neurons and synapses. The integration of neuromorphic computing with emerging technologies, such as resistive random-access memory (RRAM), further paves the way for scalable systems capable of handling the increasing complexity and volume of data in Industry 5.0 supply chains (Abbas et al., 2022; Ielmini & Milo, 2017; Pecqueur et al., 2018).

Various algorithms and frameworks have been employed to train SNNs and solve specific applications, including reservoir computing, spike-timing-dependent plasticity (STDP), and graph theory approaches (Liu et al., 2021; Pritchard et al., 2023; Schuman et al., 2022; Tavanaei et al., 2018; Yamazaki et al., 2022). Reservoir computing, for instance, involves using a sparsely connected recurrent SNN as a "liquid" or reservoir, eliminating the need to train the SNN component and finding applications in bio-signal processing, prosthetic control, and video and audio signal processing (Schuman et al., 2022). STDP, on the other hand, is a learning rule that adjusts synaptic strengths based on the timing of pre-and post-synaptic spikes, enabling SNNs to adapt and learn effectively in tasks such as pattern recognition and classification (Liu et al., 2021; Pritchard et al., 2023; Tavanaei et al., 2018; Yamazaki et al., 2022). Software frameworks such as Brain2, Nest, Nengo, SpykeTorch, BindsNet, and GeNN provide comprehensive tools for developing, simulating, and testing SNN models (Yamazaki et al., 2022). These frameworks facilitate the design and implementation of neuromorphic systems, allowing researchers and practitioners to explore the potential of neuromorphic computing in various domains, including supply chain management.

In the Industry 5.0 supply chain management context, neuromorphic computing offers significant advancements in energy efficiency, speed, and noise resilience, as demonstrated by advanced neuromorphic systems like SpiNNaker and Loihi (Schuman et al., 2022). The proposed Neuromorphic Adaptive Topological Risk Management (NAToRM) system leverages these capabilities to address the challenges of big data analytics, real-time decision-making, and risk management in Industry 5.0 supply chains (Abderrahmane et al., 2020; Aimone et al., 2022; Aitsam et al., 2022; Hendy & Merkel, 2022; Park & Kim, 2023). By integrating neuromorphic computing with persistent homology and spatiotemporal risk matrices, the NAToRM system presents a novel approach to navigating the complexities of modern supply chains, enabling organizations to optimize operations, mitigate risks, and enhance overall supply chain resilience. Despite the progress in neuromorphic computing, challenges remain in developing efficient training algorithms and seamlessly integrating neuromorphic systems with existing computing infrastructures (Liu et al., 2021; Pritchard et al., 2023; Yamazaki et al., 2022). However, ongoing research in advanced materials, such as memristors and organic artificial synapses, and the development of spike-based neuromorphic computing platforms indicate a promising future for this field (Ahmed et al., 2023; Calandra Sebastianella et al., 2021; Cheng et al., 2022; Hendy & Merkel, 2022;

Krestinskaya et al., 2020; Xiao & Huang, 2016). As research continues to push the boundaries of neuromorphic computing, these systems are expected to become increasingly capable of handling the demands of Industry 5.0 supply chains, contributing to the development of more sustainable, efficient, and resilient supply networks.

The NAToRM system, which integrates neuromorphic computing with persistent homology and spatiotemporal risk matrices, presents a novel approach to address the complexities of data analysis and risk management in Industry 5.0 supply chains. This interdisciplinary endeavor highlights the potential of neuromorphic computing to contribute to the sustainability and automation of supply chain management, aligning with Industry 5.0 (Koh et al., 2019). The literature reviewed in this section establishes the relevance of neuromorphic computing for the current research. It provides a foundation for discussing the theoretical implications and practical contributions of the NAToRM system within the context of existing literature. As Industry 5.0 continues to shape the future of supply chain management, the integration of neuromorphic computing, as exemplified by the NAToRM system, holds immense potential for driving innovation, efficiency, and sustainability. By leveraging the principles of biological neural networks, neuromorphic computing offers a powerful toolset for tackling the challenges posed by the increasing complexity and dynamism of modern supply chains. The literature reviewed in this section underscores the significance of neuromorphic computing in the context of Industry 5.0 and sets the stage for further exploration of its applications in supply chain management.

3. Deciphering complex data patterns: progress in topological data analysis and the robustness of persistent homology

Topological Data Analysis (TDA) is a sophisticated mathematical framework that integrates techniques from algebraic topology and computational geometry to dissect and comprehend complex datasets, particularly those obscured by noise and high dimensionality (Carlsson & Zomorodian, 2009). TDA transforms data into a topological space, revealing topological features such as connected components, holes, and voids. The innovative concept of persistent homology is central to TDA, gauging topological features' persistence over various scales. Persistent homology excels in handling high-dimensional and noisy data, providing a more accurate and comprehensive analysis of the data's topological structure (Carlsson & Zomorodian, 2009; Zomorodian & Carlsson, 2005). The theoretical underpinnings of persistent homology are rooted in algebraic topology, where homology imparts algebraic invariants to topological spaces (Chazal & Michel, 2021). A fundamental step is the construction of simplicial complexes, which are abstract representations reflecting the interconnections among data points. Filtration incrementally reveals the topology of data at different levels of detail, and the calculation of homology groups uncovers multidimensional features (Carlsson, 2009; Huber, 2021).

3.1. Investigating persistent structures and implementing computations

Persistent homology uses persistent vector spaces and persistence diagrams to capture, quantify, and visualize topological features at diverse scales (Chazal & Michel, 2021). Persistent vector spaces arise from the construction of homology groups through filtration, whereas persistence diagrams offer a graphical representation of the birth and death of topological features (Carlsson & Zomorodian, 2009; Otter et al., 2017). These tools enable a profound comprehension of the intrinsic structure of data across scientific and engineering fields (Otter et al., 2017). The computation of persistent homology involves constructing a filtration of the dataset based on a distance or similarity measure, capturing the gradual emergence and disappearance of topological features (Carlsson & Zomorodian, 2009; Chazal & Michel, 2021; Huber, 2021). Efficient algorithms, such as the "ripser" algorithm, are employed to calculate Betti numbers and track the persistence of topological features across scales (Chazal & Michel, 2021; Otter et al., 2017; Zomorodian & Carlsson, 2005).

3.2. Multidimensional data analysis and challenges

Multidimensional data analysis deciphers datasets with multiple dimensions to reveal patterns, relationships, and structures. Carlsson and Zomorodian (2009) explored the concept of multidimensional persistence, highlighting the lack of a complete discrete invariant. Various techniques, such as dimensionality reduction methods (principal component analysis [PCA], multidimensional scaling [MDS]) and clustering algorithms, are used to address these challenges (Chazal & Michel, 2021). Persistent homology is a powerful tool in multidimensional data analysis that is capable of analyzing topological structures across different scales (Otter et al., 2017). It offers a comprehensive view of the data's global structure by considering the persistence of topological features (Zomorodian & Carlsson, 2005). The applications of persistent homology span diverse fields, including biology, computer vision, materials science, and social network analysis (Chazal & Michel, 2021; Huber, 2021). However, multidimensional persistence faces various challenges, including computational complexity, parameter selection, noise, uncertainty, interpretation, visualization, and ensuring stability and robustness (Carlsson & Zomorodian, 2009; Chazal & Michel, 2021; Huber, 2021; Otter et al., 2017). The absence of a complete discrete invariant for multidimensional persistence presents an obstacle for comprehensively characterizing topological features within multidimensional datasets (Carlsson & Zomorodian, 2009). Despite these challenges, persistent homology remains a potent analytical tool in multidimensional data analysis. Ongoing research focuses on developing new algorithms and techniques to enhance the practicality and accuracy of persistent homology across various domains. By confronting these challenges, researchers can unlock the full potential of persistent homology, allowing more profound insights into the structure and shape of complex datasets.

4. Spatiotemporal risk matrices: a versatile tool for risk analysis and management

Spatiotemporal risk matrices are sophisticated analytical tools that assess and visualize risks across spatial and temporal dimensions. These matrices have found widespread application in diverse fields, including public health, environmental science, disaster management, urban planning, epidemiology, ecology, meteorology, medicine, transportation, and forestry (C. Zhou et al., 2023; Coletti et al., 2020; Fontecha et al., 2021; Hui, 2022; Ma et al., 2017; Omer et al., 2014; Podaras et al., 2021; Pramudhita & Santoso, 2022; T. Xiao et al., 2022; Wang et al., 2021; Yoo et al., 2022). By integrating spatial data that maps risks across different geographic locations with temporal data tracking risk evolution over periods such as days, weeks, months, or years, spatiotemporal risk matrices provide a multifaceted approach to risk evaluation and management. The spatial aspect of these matrices pinpoints areas at higher risk of specific events, while the temporal data enriches the analysis by revealing how risks evolve, aiding in forecasting and monitoring risk evolution. In public health, spatiotemporal risk matrices help identify emerging health crises for targeted interventions. Environmental scientists use them to monitor deforestation, predict the spread of invasive species, and assess the impacts of climate change on biodiversity. Disaster management professionals rely on these matrices to prepare for and respond to natural disasters by identifying vulnerable regions and optimizing response strategies. Urban planners integrate risk assessments into infrastructure development to enhance resilience against various hazards. In transportation, spatiotemporal risk matrices assist in pinpointing accident-prone areas to improve road safety and plan safer networks. Forestry benefits from their use in monitoring forest fire risks and managing forest health. The versatility of spatiotemporal risk matrices across numerous domains underscores their critical role in risk evaluation and management. This paper explores the multifaceted applications of these matrices, discusses the challenges in their construction and interpretation, and highlights future directions for enhancing their utility and impact. By providing a comprehensive overview of spatiotemporal risk matrices, this research seeks to contribute to the theoretical understanding and practical application of these tools in risk analysis and management, with implications for sustainability and automation in various fields.

4.1. Spatiotemporal risk matrices: construction, applications, and challenges

Spatiotemporal risk matrices are sophisticated analytical tools that integrate spatial and temporal data to assess and visualize risks across various dimensions. The development of these matrices begins with extensive data collection from diverse sources, such as satellite imagery, sensor networks, surveys, and administrative records (De Angeli et al., 2022; Pramudhita & Santoso, 2022). The collected data undergoes processing to ensure accuracy and consistency, addressing challenges like data normalization, handling missing values, and spatial interpolation (Podaras et al., 2021; Zhang et al., 2021). Risk metrics are then computed for each spatiotemporal unit using selected models or algorithms tailored to the assessed risks, providing quantitative measures such as incidence rates, probability of occurrence, and severity of impact (Fontecha et al., 2021; T. Xiao et al., 2022; Y. Yang & Christakos, 2015). The calculated risk metrics are organized into a matrix format, transforming raw data and computed metrics into a structured form that decision makers can easily interpret. Visualization techniques, such as maps and heat maps, play a vital role in intuitively rendering spatiotemporal risk patterns (Pramudhita & Santoso, 2022).

Spatiotemporal risk matrices are multidisciplinary tools that enhance decision-making processes across various fields. In public health and epidemiology, these matrices enable early detection of disease outbreaks and an understanding of disease spread and incidence patterns (Jaya et al., 2022; Wah et al., 2020; Wang et al., 2021). Urban planners and disaster management professionals use these matrices to identify areas at risk of natural disasters and guide the development of resilient infrastructure and emergency services (Fontecha et al., 2021; Zhou et al., 2023). In transportation, spatiotemporal risk matrices analyze traffic accident data to uncover patterns and inform targeted safety measures (Kashifi et al., 2022). Environmental scientists apply these matrices to monitor and predict the impact of climate change on biodiversity, the spread of invasive species, and forest fire risks (Li et al., 2022; Ren et al., 2022). The general risk matrix, a fundamental tool in risk management, employs a straightforward, tabular form to map out the risk landscape based on the severity of potential damage and the probability of its occurrence (Duijm, 2015; Sutherland et al., 2021). Spatiotemporal risk matrices build upon this foundational structure, introducing a more complex and nuanced approach to risk assessment by incorporating spatial and temporal dimensions. This advanced adaptation captures the dynamic nature of risks that vary across locations and over time and are influenced by environmental changes, urban development, and seasonal variations. The complexity and depth of analysis in spatiotemporal risk matrices necessitate the use of specialized software for visualization and analysis (Atasoy et al., 2022). Spatiotemporal risk matrices present challenges because of the dynamic nature of risks, where factors such as environmental changes, urbanization, population movements, and climate variability can influence risk patterns in unpredictable ways (Hui, 2022; Pramudhita & Santoso, 2022). The complexity of these matrices necessitates high expertise in data analysis, statistical modeling, and domain-specific knowledge to ensure accurate reflection of risks and meaningful findings (Xiao et al., 2022; Zhang et al., 2021). The interpretation of spatiotemporal risk matrices must be cautiously approached, considering the assumptions and limitations of the underlying data and models (Atasoy et al., 2022; Duijm, 2015; Sutherland et al., 2022).

4.2. Navigating complexities and future directions

Spatiotemporal risk matrices have emerged as pivotal tools in various sectors, offering a nuanced lens through which risks can be assessed and managed (Coletti et al., 2020; De Angeli et al., 2022). However, the path forward is fraught with challenges, such as the complexity of integrating multifaceted spatial and temporal data, which can oversimplify the dynamics at play (Messier & Katzfuss, 2021; Omer et al., 2014). The rapid evolution of risk factors necessitates continuous updates and methodological refinements in spatiotemporal risk matrices, integration of evolving data streams, and adoption of advanced computational techniques (Dong et al., 2015; Poplin et al., 2018; Yoo et al., 2022). This is particularly relevant in dynamic environments like supply chains, where risks are constantly evolving and require a comprehensive approach to maintain resilience and sustainability (Hui, 2022; Pramudhita & Santoso, 2022; T. Xiao et al., 2022; Zhang et al., 2021). Ethical considerations and privacy concerns represent another critical challenge that requires rigorous adherence to ethical standards and privacy regulations (Ren et al., 2022). Because spatiotemporal risk matrices often involve collecting and analyzing sensitive information, it is crucial to ensure that data are handled responsibly, with appropriate safeguards in place to protect individual privacy and prevent misuse.

Integrating spatiotemporal risk matrices with other information systems, such as Geographic Information Systems (GIS) and real-time monitoring platforms, will enhance their utility within a comprehensive risk management framework (Coletti et al., 2020). This integration allows for a more seamless flow of information and enhances the matrices' role in informing risk mitigation and management strategies. Future research should focus on refining the ability of spatiotemporal risk matrices to model complexity more accurately and enhance their integration with other decision-support systems. Advancements in computational techniques such as deep learning, artificial neural networks, and Bayesian models show promise in improving the predictive power of these matrices (Jaya et al., 2022; Poplin et al., 2018; Yang & Christakos, 2015). As the complexity of multidimensional datasets increases, there is a growing need for spatiotemporal risk matrices that can handle large volumes of data and provide accurate predictions. Effective communication and visualization of the insights derived from spatiotemporal risk matrices are crucial for their widespread adoption and use. Clear and intuitive interfaces and strategies for disseminating information to diverse audiences will ensure that stakeholders can understand and act upon the findings. Training and capacity building will also play a vital role in successfully applying these tools across various domains. The future of spatiotemporal risk matrices lies in their ability to adapt and evolve within an ever-changing risk landscape. By embracing advancements in technology, data analytics, and ethical practices and prioritizing user engagement and practical applicability, these matrices can become even more effective tools for managing complex risks in the modern world. A multidisciplinary approach that combines data science, domain-specific knowledge, and stakeholder engagement will be vital to realize the full potential of spatiotemporal risk matrices in fostering resilience and sustainability across various sectors.

5. Dynamics of decision-making in reinforcement learning: framework, tasks, challenges, and advanced solutions

Reinforcement learning (RL) is a transformative branch of artificial intelligence (AI) that empowers autonomous agents to learn optimal behaviors through interactions with their environments. This learning paradigm mirrors the natural learning mechanisms observed in humans and animals, where agents make decisions that maximize cumulative rewards over time. The decision-making framework of RL is structured around the agent's and environment's interaction, characterized by a series of states that can vary from fully observable to partially observable (Bilgin, 2020; Glassner, 2021). In fully observable states, agents have complete information about the environment, facilitating straightforward decision-making processes. Conversely, partially observable states require agents to make decisions with incomplete information, necessitating inference and probabilistic reasoning to navigate uncertainties. The agent's learning process is inherently iterative and adaptive, with each decision and subsequent feedback serving as a critical learning moment. Positive feedback reinforces successful strategies, whereas negative feedback prompts reevaluation and adjustment of strategy (Bilgin, 2020; Glassner, 2021). Learning through rewards is the driving force behind an agent's ability to make informed decisions. Immediate rewards provide feedback on the direct consequences of actions, whereas long-term rewards focus on cumulative benefits over extended periods. Balancing these rewards is crucial for securing optimal long-term outcomes (Bilgin, 2020).

5.1. Episodic and continuing tasks, dynamic learning, and challenges

RL tasks are categorized as episodic and continuing tasks. Episodic tasks have a finite horizon, with a clear starting point and a terminal state marking the end of an episode. The agent's mission is to maximize the cumulative rewards within each episode. In contrast, continuing tasks represent an open-ended engagement that requires the agent to maintain optimal performance indefinitely (Bilgin, 2020). Agents engage in a dynamic process of strategy adaptation driven by continuous interaction between the agent and its environment. Central to this dynamic learning approach is the agent's capacity to interpret and respond to feedback, adjust strategies to enhance performance, and maximize cumulative rewards. Strategy adaptation involves a delicate balance between exploring new techniques and exploiting known successful ones (Bilgin, 2020; Glassner, 2021). RL presents pivotal challenges like the credit assignment problem and the explore-exploit dilemma. The credit assignment problem pertains to identifying which actions among a sequence of decisions directly contribute to eventual outcomes. The explore-exploit dilemma captures the strategic balancing act between exploring new actions to uncover potentially more rewarding strategies and exploiting known actions that have previously led to positive outcomes (Bilgin, 2020).

5.2. Addressing the challenges and sophistications of reinforcement learning

A sophisticated approach to mitigating the credit assignment problem involves using discounted future rewards (DFR), which assign value to actions based on their anticipated contributions to future successes. The discount factor, denoted as γ (gamma), calibrates the agent's sensitivity to future rewards on the basis of their expected reliability and occurrence. By adjusting the γ value, RL agents can modulate their confidence in the consistency and predictability of future rewards, strategically balancing the pursuit of immediate rewards with attaining long-term goals (Glassner, 2021). The sophistication of RL in AI decision-making lies in its emphasis on experiential learning, strategic adaptation, and careful balancing of immediate and long-term rewards. Through its innovative approaches to learning and decision making, RL demonstrates significant potential for navigating the complexities of real-world scenarios, offering a versatile and robust framework for developing AI systems capable of sophisticated, strategic, and adaptable decision making (Bilgin, 2020; Glassner, 2021).

6. The transformative approach of NAToRM in Industry 5.0 supply chain management

The Neuromorphic Adaptive Topological Risk Management (NAToRM) system is a groundbreaking approach in the Industry 5.0 era, heralding a new paradigm in supply chain management that is attuned to the nuances of human-centric automation, sustainability, and the integration of advanced technologies. NAToRM tackles the intricate challenges of contemporary supply chains through a strategic combination of neuromorphic computing, persistent homology, and spatiotemporal risk matrices. This innovative framework enhances operational efficiency and risk management and maximizes the utility of extensive data generated across supply chains. Neuromorphic computing, inspired by the neural architecture of the human brain, is pivotal for NAToRM's ability to process data at unparalleled speeds and manage parallel data streams. Its adaptive learning capacity allows it to evolve operational paradigms in real time, responding adeptly to emergent patterns and changes within the supply chain environment. Persistent homology is a sophisticated analytical tool that leverages the principles of topological data analysis to uncover hidden structures and relationships within complex datasets, providing invaluable insights for strategic decision making. The spatiotemporal risk matrix revolutionizes risk assessment by offering a methodical approach to integrating and analyzing spatial and temporal data, ensuring the agility and adaptability of supply chain operations. At the core of the NAToRM framework, the RL algorithm continuously adapts and learns from the system's evolving spatiotemporal scenarios, aligning NAToRM with strategic supply chain decisions and optimizing resource allocation and logistical operations for enhanced efficiency. NAToRM redefines the supply chain management landscape by balancing operational efficiency, effective risk management, and a commitment to customer-centricity.

6.1. Integration and strategic impact of NAToRM in industry 5.0 supply chains

The NAToRM system exemplifies a groundbreaking shift in the supply chain management paradigm for Industry 5.0. This advanced framework unites neuromorphic computing, persistent homology, and spatiotemporal risk matrices to create a comprehensive and integrated approach that addresses the intricacies and demands of modern, highly automated supply chains. The strategic impact of NAToRM's integration within Industry 5.0 supply chains is multifaceted, focusing on three core areas:

1. Comprehensive Data Analysis: NAToRM's approach combines the advanced processing capabilities of neuromorphic computing with the deep analytical insights of persistent homology to revolutionize supply chain management. The synergy between these technologies ensures that supply chains benefit from a comprehensive data analysis framework, empowering managers to make decisions based on the most current and complete data.
2. Enhanced Risk Management: NAToRM's enhanced risk management is exemplified through the innovative integration of the spatiotemporal risk matrix, which merges spatial and temporal data to provide a comprehensive and dynamic risk assessment across global supply chains. The RL algorithm's predictive analytics further enhance this capability, ensuring that supply chains are proactively prepared to handle the inherent uncertainties of worldwide trade and market demands.
3. Proactive and Adaptive Operations: NAToRM revolutionizes supply chain management by imbuing operations with proactive and adaptive capabilities, primarily through the sophisticated application of its RL algorithm. This strategic adaptation ensures that supply chains react to immediate challenges and are equipped to handle future complexities, facilitating a proactive supply chain management model that enables organizations to effectively navigate the complexities and volatilities of the global market.

The strategic integration of the NAToRM framework within Industry 5.0 supply chains heralds a significant leap forward in enhancing global commerce networks' intelligence, resilience, and adaptability. This cutting-edge approach employs the latest in AI and data analytics to revolutionize supply chain management, offering a comprehensive solution that aligns with the complex, interconnected nature of today's market demands.

6.2. Challenges and future directions

Implementing the NAToRM system signifies a groundbreaking advancement in Industry 5.0 supply chain management, but it also presents challenges and future considerations. Deploying NAToRM requires significant investment in cutting-edge technology and infrastructure and continuous updates and meticulous maintenance to ensure its practicality and relevance. The system's complexity and reliance on advanced AI and computing technologies also pose challenges regarding flexibility and scalability, demanding robust technological support and a commitment to ongoing development. Despite these hurdles, NAToRM offers strategic foresight and adaptability, making it an invaluable asset for navigating the complexities of contemporary and future supply chain management. Its forward-looking approach anticipates and adapts to the changing landscape of global supply chains, which is characterized by increasing interconnectedness, technological advancements, and the need for sustainability and human-centric automation. Looking ahead, NAToRM's role in the future of supply chain management is poised for significant impact. Its ability to provide a holistic, integrated approach to managing complex supply chain dynamics offers a blueprint for resilience, efficiency, and strategic agility in the Industry 5.0 era. While NAToRM presents challenges in implementation and demands a commitment to ongoing innovation and maintenance, its strategic advantages and potential for transformative impact on supply chain management are undeniable.

7. Discussion

The advent of Industry 5.0 ushers in a transformative era in supply chain management, marked by a shift toward the integration of advanced technologies such as neuromorphic computing, persistent homology, and spatiotemporal matrices. These technologies herald a fundamental change in how supply chain data is processed and used, unlocking meaningful and actionable insights from the vast, diverse, and complex data generated in modern supply chains. The current paper contributes to the growing body of literature on Industry 5.0 supply chain management by presenting a novel multidisciplinary framework that integrates cutting-edge techniques to address the challenges associated with big data analytics, technology integration, and ethical considerations (Ateş et al., 2021; Govindan et al., 2021). Neuromorphic computing, with its ability to mimic the human brain's processing capabilities, persistent homology's TDA approach, and spatiotemporal matrices' contextual data analysis, presents innovative ways to meet the demands of modern supply chains. The findings of this paper align with previous research highlighting the potential of these technologies to enable a more nuanced understanding of supply chain dynamics by analyzing data that accounts for its multidimensional and interconnected nature (Carlsson & Zomorodian, 2009; Coletti et al., 2020; Schuman et al., 2022). The integration of these technologies into the proposed NAToRM framework drives efficiency and strategic decision-making in an increasingly data-driven world, addressing the need for comprehensive frameworks that ensure data integrity, uphold privacy regulations, and promote stakeholder collaboration (Elezaj & Tole, 2018; Noviyanti et al., 2020; Struijs et al., 2014).

Neuromorphic computing is rapidly becoming a linchpin technology in Industry 5.0, redefining the approach to data processing in supply chain management. This paper builds upon previous research by demonstrating the transformative potential of neuromorphic computing in the NAToRM system for Industry 5.0 supply chain management (Abderrahmane et al., 2020; Aimone et al., 2022; Aitsam et al., 2022). The advanced neural network architecture of neuromorphic computing enables rapid identification of emerging patterns and anomalies within data streams, and its adaptability and speed allow quick adaptation to new data and informed decision-making. Neuromorphic computing's capacity for parallel processing effectively handles the multifaceted nature of supply chain data, leading to more comprehensive and holistic insights. Persistent homology, a complementary force alongside neuromorphic computing, offers a profound enhancement in data analysis for supply chain management. The findings of this paper extend the applications of persistent homology to the domain of supply chain management, demonstrating its ability to delve into the intricate structures and patterns within data, uncovering hidden layers of information (Carlsson, 2009; Zomorodian & Carlsson, 2005). Persistent homology explores the topological features of datasets, revealing significant patterns and relationships that might not be obvious through traditional data analysis methods. It aids in identifying areas that require attention or improvement, facilitating more informed and strategic decision-making. Integrating spatiotemporal matrices into supply chain analysis represents a significant advancement in understanding and using supply chain data. The current paper contributes to the growing body of literature on spatiotemporal risk matrices by demonstrating their versatility and potential in supply chain management (Coletti et al., 2020; Omer et al., 2014; Wang et al., 2021). By combining geographical and temporal dimensions, these matrices add a crucial layer of context to supply chain management, enabling a more comprehensive understanding of the various factors influencing supply chain dynamics. Spatiotemporal matrices offer a dynamic view of supply chain operations, aligning analysis with the real-world movement and evolution of goods, information, and trends. They facilitate targeted and timely interventions, transforming supply chain management into a more proactive and strategic function. RL emerges as a transformative approach to supply chain management, optimizing decision-making processes in complex and uncertain environments. The findings of this paper align with previous research highlighting the potential of RL to handle the multi-objective nature of supply chains, balance competing goals, and facilitate more personalized and responsive customer service (Bilgin, 2020; Glassner, 2021). RL's iterative learning process allows agents to discover efficient strategies for inventory management, demand forecasting, and logistics planning, adapting to changes in the supply chain without the need for explicit reprogramming. By leveraging the power of RL, supply chain managers can navigate the complexities of Industry 5.0 with greater agility and intelligence.

7.1. Challenges and future directions

Integrating neuromorphic computing, persistent homology, and spatiotemporal matrices into supply chain management presents a transformative approach to tackling Industry 5.0′s complexities, but it also poses significant challenges that require meticulous attention. The current paper contributes to the ongoing discussion on the challenges and future directions of integrating advanced technologies in supply chain management by emphasizing the need for developing a cohesive framework that enables these technologies to work synergistically (Ateş et al., 2021; Dwivedi et al., 2021; Koh et al., 2019). This necessitates deep technological expertise and a robust understanding of supply chain dynamics to facilitate enhanced decision-making and efficiency. In addition, extensive real-world testing is crucial to ensure practical viability and adaptability to various supply chains, helping to refine these technologies to meet specific operational demands. The paper also highlights the ethical and social implications concerning data privacy, security, and algorithmic bias, calling for robust governance frameworks and cybersecurity measures to protect sensitive information and ensure fairness and transparency in automated decisions. These findings align with previous research, which emphasizes the need for comprehensive ethical guidelines to ensure the responsible deployment of advanced technologies in supply chain management (Elezaj & Tole, 2018; Noviyanti et al., 2020; Struijs et al., 2014). Moreover, the paper underscores the importance of a collaborative approach involving industry leaders, policymakers, and academics to address these challenges comprehensively, promoting continuous innovation and adaptation to maintain pace with evolving global supply chain demands. Successfully integrating these advanced technologies promises to revolutionize supply chain management by improving predictive analytics and real-time decision-making and ensures a responsible and sustainable transition in the era of Industry 5.0.

7.2. Implications of the NAToRM framework for supply chain management

The NAToRM framework has far-reaching implications for supply chain management in the Industry 5.0 era, offering both practical benefits and theoretical contributions. The current paper contributes to the emerging paradigm of Industry 5.0 by presenting a pioneering effort to integrate cutting-edge technologies into a cohesive framework tailored to the unique challenges of Industry 5.0 supply chains (Bednar & Welch, 2020; European Commission, 2021). NAToRM revolutionizes operational efficiency by leveraging the capabilities of neuromorphic computing, enabling real-time data processing and adaptive decision-making. It improves risk management by employing persistent homology to identify complex patterns and potential disruptions within the supply chain. Integrating spatiotemporal matrices into NAToRM enhances the framework's practical utility, providing a comprehensive view of supply chain risks across geographical and temporal dimensions. Incorporating RL facilitates optimized resource allocation and reduces downtime, leading to potential cost savings for organizations. The NAToRM framework also contributes significantly to the theoretical landscape of supply chain management research, aligning with the emerging paradigm of Industry 5.0, which emphasizes human-centric automation and sustainability (Geissdoerfer et al., 2017; Koh et al., 2019). This paper highlights the critical role of interdisciplinary collaboration in addressing the complex challenges faced by modern supply chains, setting the stage for future research on the ethical and social implications of advanced technologies in supply chain management (Elezaj & Tole, 2018; Noviyanti et al., 2020; Struijs et al., 2014). The NAToRM framework provides a platform for exploring these issues and developing responsible governance frameworks, contributing to the ongoing discourse on sustainable and responsible supply chain management in the era of Industry 5.0 (Figs. 1, 2 and 3).

8. Limitations

Integrating neuromorphic computing and TDA into sustainable supply chain management presents a promising avenue for addressing the complexities of Industry 5.0. However, this integration is not without its challenges. One of the primary concerns is the computational complexity inherent in multidimensional persistence, which is a cornerstone of TDA. As data dimensionality increases, so do computational demands, which require the development of efficient algorithms and customization to align with diverse supply chain requirements. In addition, selecting appropriate parameters for defining simplicial complexes and handling noisy or incomplete data are crucial for ensuring the accuracy and reliability of the insights derived from these technologies. Visualization and interpretation of complex data structures and results from persistent homology also become more challenging as data dimensionality increases, necessitating the development of practical visualization tools. Moreover, integrating neuromorphic computing and TDA into sustainable supply chain management raises critical ethical considerations. Concerns over data privacy, security, and the potential for job displacement highlight the need for comprehensive ethical guidelines to ensure the responsible deployment of these technologies. Collaborative challenges also emerge due to differences in terminologies, methodologies, and objectives across various disciplines, such as computer science, engineering, supply chain management, and ethics. These differences can limit innovation and the generalizability of findings, emphasizing the importance of interdisciplinary collaboration to foster a more holistic and effective integration of these technologies. Collaborative efforts among academia, industry, and regulatory bodies are essential to address these limitations and fully realize the potential of neuromorphic computing and TDA in revolutionizing sustainable supply chains. We can develop solutions to overcome computational, methodological, and collaborative challenges by fostering interdisciplinary research teams and prioritizing ethical considerations. This approach will not only help mitigate the limitations but also set a new standard for leveraging technology to address global supply chain challenges, ultimately leading to enhanced sustainability and efficiency in Industry 5.0.

9. Conclusion

This paper presents a groundbreaking multidisciplinary framework that integrates neuromorphic computing, persistent homology, spatiotemporal matrices, and RL to address the critical challenges Industry 5.0 supply chains face in managing big data effectively while ensuring sustainability, privacy, and ethics. The proposed approach sets new data-driven operational benchmarks by leveraging real-time data analysis, uncovering deep insights, understanding supply chain risks, and enabling dynamic decision-making. The framework signifies a paradigm shift toward resilient, intelligent, and adaptable supply chains that navigate Industry 5.0 challenges, aligning with the emerging paradigm of Industry 5.0 and contributing to the growing body of literature on sustainable and responsible supply chain management (Bednar & Welch, 2020; Anon., European Commission, 2021; Geissdoerfer et al., 2017; Koh et al., 2019). The practical implementation of this framework requires extensive research and development, thorough real-world testing, and robust integration frameworks. Successfully integrating

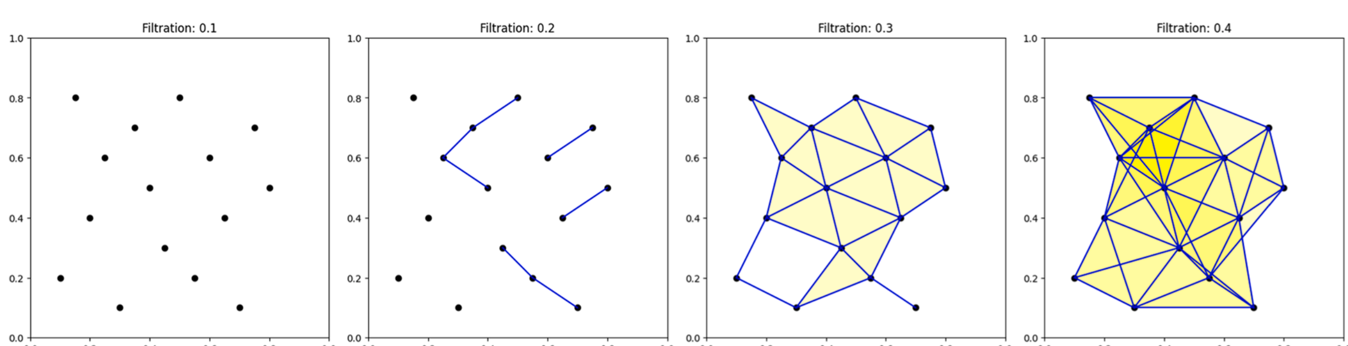

Fig. 1. Sequential Development of Simplicial Complexes in Topological Data Analysis. This figure depicts the step-by-step construction of simplicial complexes at critical filtration stages (0.1, 0.2, 0.3, and 0.4), illustrating the evolution of topological features such as connected components, holes, and voids within a point cloud dataset. Each stage provides progressively deeper insights into the dataset's underlying topological structure, which is essential for understanding multidimensional persistence among the challenges of noisy, high-dimensional data.

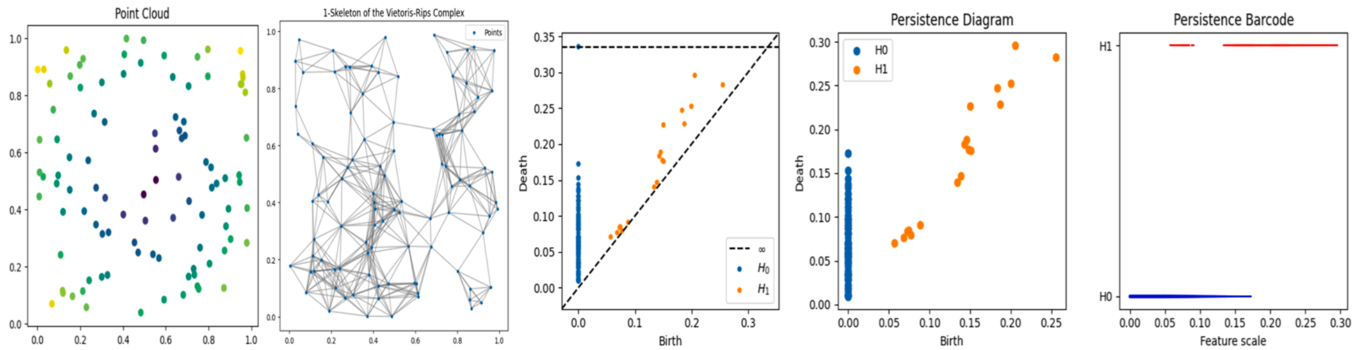

Fig. 2. Comprehensive Workflow of Topological Data Analysis Using Ripser. This figure displays, from left to right, the stages of processing point cloud data through the Ripser software: initial data representation, construction of the Vietoris-Rips complex at a selected filtration scale, a persistence diagram depicting the lifecycle ('birth' and 'death') of topological features, and a persistence barcode that encapsulates the durability of these features over varying scales. This sequence provides a step-by-step visualization of how complex data are transformed into analyzable topological insights, which is essential for the robust analysis of high-dimensional datasets.

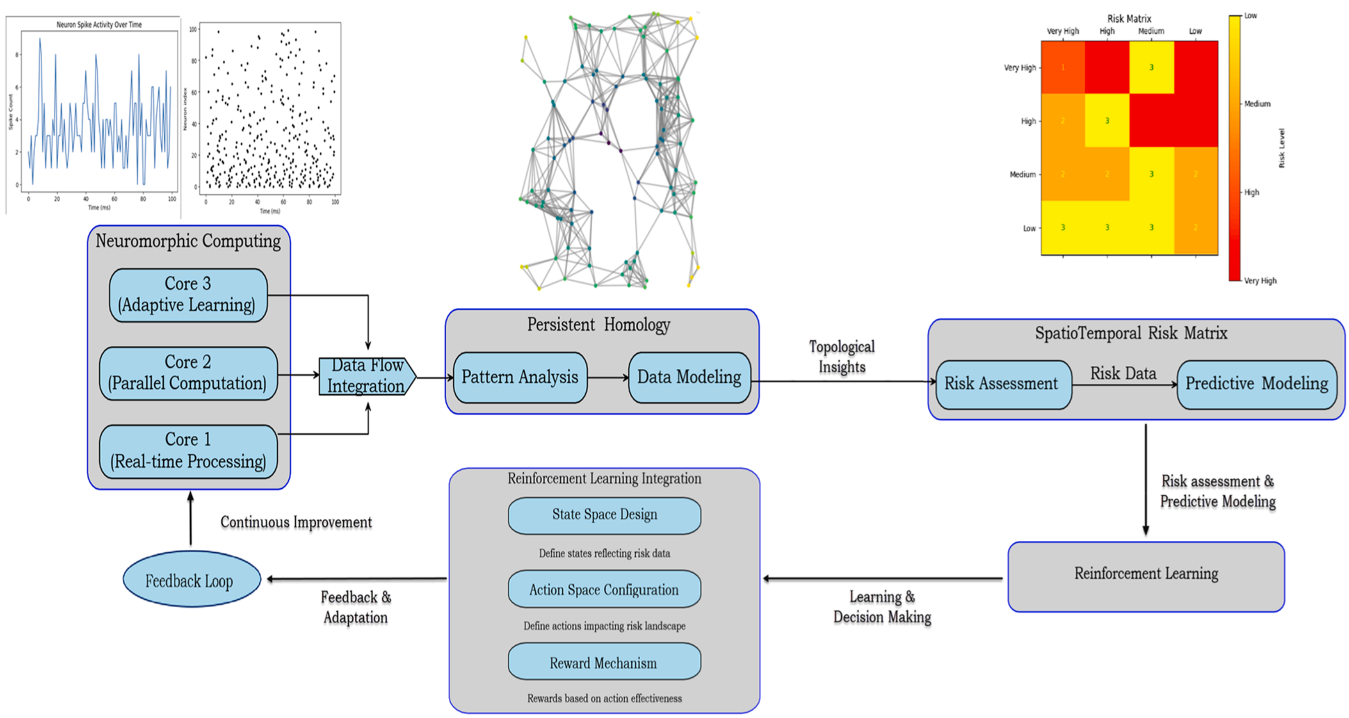

Fig. 3. NAToRM Framework. This diagram illustrates the integrated framework of the Neuromorphic Adaptive Topological Risk Management (NAToRM) system, showcasing the synergy among neuromorphic computing, persistent homology, the spatiotemporal risk matrix, and the reinforcement learning algorithm within Industry 5.0 supply chains.

these advanced technologies promises to revolutionize supply chain management by improving predictive analytics and real-time decision-making and ensures a responsible and sustainable transition in the era of Industry 5.0. The ability to quickly process and interpret vast amounts of complex data will distinguish leaders in this field. With its combination of neuromorphic computing, persistent homology, spatiotemporal matrices, and RL, the proposed framework is set to revolutionize supply chain management by addressing the multifaceted challenges of big data analytics, technology integration, and ethical considerations (Ateş et al., 2021; Govindan et al., 2021). This advancement tackles the multifaceted challenges of big data, fostering collective innovation, and shaping the future of Industry 5.0 supply chains. This paper contributes to the ongoing discourse on the integration of advanced technologies in supply chain management, highlighting the need for interdisciplinary collaboration and emphasizing the ethical and social implications of these technologies (Dwivedi et al., 2021; Elezaj & Tole, 2018; Koh et al., 2019; Noviyanti et al., 2020; Struijs et al., 2014). Navigating this transformation will be intricate and demanding, requiring ongoing adaptation to new technologies and market dynamics. Nonetheless, the potential to redefine supply chains in the age of Industry 5.0 presents an essential and compelling journey for researchers, technologists, and industry practitioners, setting the stage for future research on the responsible and sustainable integration of advanced technologies in supply chain management.

CRediT authorship contribution statement

Steven M. Williamson: Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Victor Prybutok:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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