Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Neuromorphic Optimization in Construction Supply Chain Logistics Management

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The inefficiencies in the logistics of the supply chain in the construction industry often result in project delays, increased expenses, and resource wastage. Traditional management methods are inappropriate for the dynamic and complex environment in which construction projects are undertaken. This research delves into the potential of leveraging neuromorphic computing, inspired by the human brain's neural architecture, to optimize supply chain operations. The primary objective is to scrutinize how neuromorphic systems can elevate inventory management, logistics optimization, demand forecasting, and supplier relationship management within supply chain operations. In pursuit of this goal, A structured questionnaire survey was administered to 182 respondents from Saudi Arabia to conduct data analysis via Principal Component Analysis (PCA). PCA exposed that the AVE values at 0.554, 0.607, 0.709, and 0.655 for Inventory Management Optimization, Logistics Optimization, Demand Forecasting, and Supplier Management, respectively, established the validity and reliability of the constructs. The established path coefficients were 0.43, 0.337, 0.477, and 0.135, at $p < 0.05$. Policymakers in the field of construction logistics are encouraged to promote the adoption of neuromorphic computing in order to enhance operational efficiency, reduce costs, and achieve improved outcomes. Future research endeavours should prioritize investigating challenges associated with integration and the assurance of data security.

Keywords: Demand Forecasting; Inventory Management; Supplier Management; Logistics.

1. Introduction

Construction serves as the cornerstone of economic development, driving infrastructure growth and making a substantial contribution to the GDP of most countries. However, this diligent sector is often plagued by inefficiencies in its supply chain logistics, leading to project delays, cost overruns, and wastage of resources[1]Traditional supply chain management methods, which rely on manual procedures and linear algorithms, are insufficient to operate effectively within a construction project's dynamic and complex environment.[2]. Integrating advanced technologies is imperative to enhance supply chain efficiency and dependability within the construction industry. [3].

A satisfactory approach to address these would be through neuromorphic computing, which is part of an emerging area inspired by the neural architecture of the human brain. Neuromorphic systems are based on specialized hardware and algorithms developed to mimic the ability of brains to process information and learn from it [4]. This way, such systems enable real-time data processing, dynamic learning, and efficient decision-making, for which neuromorphic computing is best suited for undertaking complex, highly data-intensive tasks [5]. If applied to construction supply chain logistics, it may provide ways for the sector to eliminate inefficiencies and achieve higher levels of performance and sustainability[6].

As construction technology continues to advance daily, supply chain logistics is the most crucial bottleneck in construction, which often causes delays, higher costs, and mismanagement of resources [7]. The conventional mechanisms to manage supply chains have just not been enough for handling real-time processing and adaptive decision-making in the fast-paced construction environment today [8]This is a critical area in which much innovation is needed to enhance the responsiveness and efficiency of supply chain logistics in the construction industry.

Though neuromorphic computing has been demonstrated in multiple areas, such as robotics, healthcare, and finance. Despite all the great potential of neuromorphic systems, they have not been substantially applied to construction supply chain management, and few empirical studies are available. This research aims to enhance comprehension of the roles and advantages of neuromorphic optimization in construction supply chain logistics.

The general objective of this research is to determine how neuromorphic computing could optimize construction supply chain logistics. This will be achieved by:

- Optimization in Inventory Management: Real-time observation and adaptive learning are used to maintain the right stock levels and reduce waste.

- Logistics & transportation optimization: Planning cost-effective routes that ensure timely materials delivery at a site.

- Real-Time Demand Forecasting: Improved forecast accuracy through using neuromorphic algorithms for demand estimation of material and resource requirements.

- Supplier Selection & Relationship Management: Supplier selection optimization and management will be ensured in relation to material quality and on-time delivery.

This research has significant value as it addresses one critical source of inefficiency in the construction sector. Neuromorphic computing will be used to improve supply chain logistics, resulting in significant cost savings, reduced project timelines, and better resource utilization. The contribution made in this research could pave the foundation for the wide application of neuromorphic systems in construction practice and, with that, revolutionize the current practices in the construction industry.

The novelty of this research lies in applying neuromorphic computing to logistic activities in the construction supply chain, an area that has not been extensively researched. The study's implications are far-reaching, as it introduces a new paradigm for managing supply chains in construction, leading to a radical increase in efficiency and adaptability. Demonstrating practical benefits in neuromorphic optimization will likely pave the way for future innovation and technological advancement within the construction industry.

2. Literature Review

Due to its dynamic and complex nature, the challenge of getting the best supply chain logistics has been common in construction for a long time. Traditional methods fall short of dealing with the intricacies of inventory management, demand forecasting, logistics, and relationships with suppliers. The literature review focuses on the role of neuromorphic computing in addressing such challenges. It provides insight into current research, applications, and potential advantages of including neuromorphic systems in construction supply chain logistics.

Neuromorphic Computing

Neuromorphic computing is an emerging paradigm in artificial intelligence and computation that bases itself on the structure and functionality of the human brain. On the other hand, neuromorphic systems host specialized hardware and algorithms to mimic the brain's neural networks, which is different from conventional computing systems that carry out linear processing [9]. This way, real-time data processing, learning, and adaptive decision-making are allowed within neuromorphic computing, especially for solving complex data-intensive tasks. Endless efforts have been invested in trying to invent the best solutions for such tasks [10].

Inventory Management Optimization

Efficient inventory management is crucial for minimizing costs and ensuring the timely availability of materials in construction projects [11]. Traditional inventory management systems often rely on static models and historical data, which can lead to inefficiencies and stockouts [12]. Neuromorphic computing offers a dynamic solution by enabling real-time monitoring and adaptive learning dynamically [13].

Real-Time Monitoring

The systems of neuromorphic sensors and processors built within the inventory management process are structured to keep an eye on the stock levels and their use patterns on a real-time basis [14]. These systems have algorithms built with the capability to detect and analyze changes taking place in the inventory in real-time so as to bring accuracy to the information at hand [15]This provides much more accurate inventory control, which can be practiced without the risks of overstocking and stockouts.

Adaptive Learning

Neuromorphic systems can learn through historical data and ongoing operations, thereby perpetually tweaking their inventory management strategies [16]. In the pattern and trend analysis, these systems forecast future inventory needs while adjusting the reorder points as per identified adjustments [17]. learning capability guarantees optimized inventory levels, which fully meet construction projects' needs and reduce waste and storage costs.

Optimization of Logistics and Transportation

Transporting materials and equipment is one major part of supply chain logistics that is required in any construction project [18]. Complexity in routing, scheduling, and managing transport resources in traditional logistic systems makes such areas vulnerable. Logistic and transportation planning can therefore be optimized, with real-time processing and adaptive decision-making for logistic and transportation planning, through neuromorphic computing [19]. It helps in the routing and scheduling of enormous data from diversified sources, including traffic patterns, weather conditions, and project schedules [20]. These algorithms can be used to dynamically change routes and schedules, resulting in possible time savings and cost reduction in transportation. When neuromorphic systems are integrated into logistic management, construction companies are guaranteed timely and efficient delivery of all materials [21].

Resource Management

Proper management of transportation resources, such as vehicles and drivers, is critical for proper logistics. Neuromorphic systems can be used to analyze the availability of resources against the demand for the same; this can help optimize the allocation of transportation resources [22]. Dynamic resource management ensures that the right resources are availed at the right time, hence increasing the general efficiency of logistics [23].

Real-Time Demand Forecasting

Effective supply chain management within construction projects requires an excellent approach to demand forecasting, where traditional techniques used in forecasting rely on historical data and static models and, therefore, give rise to errors and inefficiencies [24]This is when neuromorphic computing for demand forecasting proves efficient. It adds an element of dynamism and, hence, sharpness to prediction.

Predictive Analytics

It can chew up vast amounts of information from sources like market trends, project timelines, and environmental conditions. Through analysis of given data, therefore, neuromorphic algorithms can provide the most accurate forecasts for future demand for materials and resources [25]. This predictive analytics capability permits construction companies to conduct further and more in-depth planning, which might reduce the likelihood of possible delays and cost overruns.

Real-Time Adjustments

Perhaps one of the critical advantages that neuromorphic computing has to offer is its capability or real-time adaptability feature. As it is, neuromorphic systems will be capable of monitoring the patterns of demand continuously and adjusting the forecasts given for such changes in real-time [26]. This being the case, it now becomes an enabling capacity that demand forecasts are accurate and updated in real-time, which in turn enables supply chain management to be more responsive and flexible.

Supplier Selection and Relationship Management

Supplier choice and supplier relationship management is a critical portion of supply chain logistics within the construction industry [27]. This adds to the fact that most traditional methods are static in the criteria they are based on and depend on historical performance data in such a way that it limits the effectiveness of supplier management. Neuromorphic computing provides a more dynamic and data-driven method for supplier selection and relationship management [13].

Supplier Performance Analysis

Algorithms developed can analyze various supplier performance data, such as quality, delivery time, and cost. Neuromorphic systems can then facilitate the real-time processing of such information and provide a full and up-to-date performance evaluation of the suppliers. Because of the dynamic appraisal of performance, construction companies can now make an informed choice on which suppliers to select [10].

Adaptive Relationship Management

Supplier relations require continual review and alignment with the performance and changes of needs projects. These can be learned from past data and ongoing interactions in adaptive relationship management strategies with the supplier for optimum supplier performance. Indiveri and Liu (2015) claim that this adaptive relationship management capability will guarantee suppliers who are consistently on par in fulfilling the project needs, improving the overall supply chain efficiency [10].

Potential Challenges and Future Research

Several challenges remain in realizing the full potential benefits of neuromorphic computing in the logistic systems of construction supply chains, and areas of future research need to be explored. These encompass integrating neuromorphic systems into available infrastructure, developing effective neuromorphic algorithms, and addressing issues of data privacy and security.

Integration into Available Infrastructure

As has been said, such an integration of neuromorphic systems into the existing supply chain infrastructure can be cumbersome and require significant human and capital resources. The construction firm must ensure compatibility of neuromorphic systems with existing technologies and systems of operation [28]. Future research has to develop a framework of standards for integration, and from there, the process of tools may make the adoption of neuromorphic computing in construction supply chain logistics much easier [29].

Development of Robust Algorithms

It is imperative to develop robust neuromorphic algorithms capable of addressing the complexity associated with construction supply chain logistics. Such algorithms should be real-time and adaptable to dynamic conditions, providing insights with a high level of precision. Further work on neuromorphic algorithm development is expected, along with future testing of those developed algorithms within construction supply chains [21].

Data Privacy and Security

A challenge that emerges following the application of neuromorphic systems within construction supply chain logistics relates to data privacy and security shown in Table 1. This indicates that neuromorphic systems are centered on processing proprietary and sensitive information, meaning data protection should be among the major concerns in research toward future secure ways of managing data and assuring that neuromorphic systems also adhere to regulations relating to relevant data privacy [30].

Table 1 Related studies with benefits and challenges.

Aspect	Description	Traditional Approach	Neuromorphic Approach	Benefits	Challenges	Future Research	Reference
Inventory Management	Monitoring and controlling stock levels	Static models based on historical data	Real-time monitoring with adaptive learning	Reduced overstock and stockouts	Integration with existing systems	Development of robust adaptive algorithms	[31]
Logistics & Transportation	Planning and managing transportation	Manual routing and scheduling	Dynamic routing and scheduling with real-time data	Reduced delays and costs	Data privacy and security	Secure data management practices	[32] [13] [10]
Real-Time Demand Forecasting	Predicting future material needs	Historical data and static models (Chen et al., 2016)	Predictive analytics with real-time adjustments (Seo et al., 2011)	Increased forecasting accuracy	Complexity of real-time data processing	Advanced neuromorphic algorithms (Merolla et al., 2014)	[30]
Supplier Selection & Relationship Management	Evaluating and managing suppliers	Static criteria and past performance	Dynamic performance analysis and adaptive strategies	Improved supplier performance and relationships	Ensuring compatibility with suppliers' systems	Standardized integration frameworks	[28] [29]
Resource Management	Allocation of transportation resources	Manual allocation	Optimized allocation with neuromorphic systems	Enhanced resource utilization	Training and adaptation	Real-world testing and validation	[33] [16]
Risk Management	Identifying and mitigating risks	Periodic assessments	Continuous monitoring and real-time response	Reduced disruptions and improved resilience	Handling large volumes of data	Scalable neuromorphic solutions	[34]
Data Integration	Combining data from various sources	Separate data silos	Integrated neuromorphic systems	Comprehensive and up-to-date information	Data compatibility issues	Integration tools and frameworks	[35]
Real-Time Monitoring	Ongoing tracking of supply chain status	Periodic manual checks	Continuous real-time monitoring	Immediate issue detection and response	High computational demands	Efficient neuromorphic hardware	[36]

Adaptive Learning	Improving system performance over time	Manual updates and adjustments	Self-learning and adapting systems	Continuous improvement in efficiency	Complexity of adaptive systems	Development of adaptive learning models	[37] [38]
Cost Reduction	Minimizing supply chain costs	Reactive cost management	Proactive optimization and efficiency (Seo et al., 2011)	Lower overall costs	Initial implementation costs	Cost-benefit analysis (Pfeil et al., 2012)	[39]
Efficiency Improvement	Enhancing overall supply chain performance	Incremental improvements	Significant gains with neuromorphic optimization	Higher efficiency and productivity	Overcoming resistance to change	Demonstrating ROI and benefits	[37]
Sustainability	Promoting sustainable practices	Limited focus on sustainability (Dubey et al., 2017)	Optimized resource use and waste reduction (Seo et al., 2011)	Improved sustainability and compliance	Balancing efficiency with sustainability	Sustainable neuromorphic solutions (Indiveri et al., 2011)	[40]

Table 2 below sets a comprehensive comparison of innovative technologies in construction project management based on their functions in real-time monitoring, predictive analytics, cost efficiency, resource optimization, risk management, sustainability, scalability, interoperability, user-friendliness, implementation cost, and innovation potential. Building Information Modeling (BIM), the Internet of Things (IoT), Artificial Intelligence (AI), Drones, 3D Printing, Virtual Reality (VR) / Augmented Reality (AR), and Neuromorphic Computing are assessed. All these technologies have a wide range of advantages in most categories, with extensive benefits in real-time data processing, predictive analytics, and resource optimization. Drones and 3D Printing assure substantive cost efficiency and resource optimization but score down significantly on risk management and scalability. VR/AR might enhance project visualization and collaboration, yet it is not strong regarding sustainability issues. Neuromorphic Computing forms a comprehensive technology subject that is well-known by virtue of being capable of real-time monitoring, adaptive learning, and sustainability, representing its capabilities to revolutionize project management in construction.

Table 2 Comparison of Neuromorphic Computing with other Advanced Technologies in Construction Project Management.

	Building Information Modeling (BIM)	Internet of Things (IoT)	Artificial Intelligence (AI)	Drones	3D Printing	Virtual Reality (VR) / Augmented Reality (AR)	Neuromorphic Computing
Real-Time Monitoring	✓	✓	✓	✓	✗	✓	✓
Predictive Analytics	✓	✓	✓	✗	✗	✗	✓
Cost Efficiency	✓	✓	✓	✓	✓	✓	✓
Resource Optimization	✓	✓	✓	✓	✓	✓	✓
Risk Management	✓	✓	✓	✗	✗	✗	✓
Sustainability	✓	✓	✓	✓	✓	✗	✓
Scalability	✓	✓	✓	✗	✓	✓	✓
Interoperability	✓	✓	✓	✗	✓	✓	✓

User-Friendliness	✓	✗	✓	✓	✓	✓	✓
Implementation Cost	✗	✗	✓	✓	✓	✓	✓
Innovation Potential	✓	✓	✓	✓	✓	✓	✓

Neuromorphic computing demonstrates a prime contribution to the enhancement of optimization in supply chain logistics within construction. Inventory management, logistics, transportation planning, demand forecasting, and management of supplier relationships would all benefit from the brain-like processing capabilities of neuromorphic systems. The application of neuromorphic computing in the logistics of a construction supply chain will make improvements in efficiency, reduce costs, and lead to better project outcomes. There are, however, several challenges in realizing the potential of neuromorphic computing into complete competency in the logistics of construction supply chains. Future work in the development of standard integration frameworks, advancement of neuromorphic algorithm development, and data privacy and security will foster the construction industry to make full use of the power of neuromorphic computing for logistic optimization of supply chains and move towards optimized performance and sustainability.

3. Methodology

Questionnaire Design and Data Collection

The sample size for this research was made up of 182 respondents from Saudi Arabia. This section presents a structured questionnaire with a Likert scale to rank the level of agreement and disagreement by the respondents on different statements, from 1 (Strongly Disagree) to 5 (Strongly Agree) [41]. A deep understanding of the factors affecting the research subject is what the questionnaire tried to delve into.

Convenience sampling was employed due to its ease and accessibility. In exploratory studies, this non-probability sampling technique is crucial for capturing a diverse range of perceptions and viewpoints. Multiple statistical analyses were conducted to strengthen the reliability of the data. This involved PCA, tests of the convergent and discriminant validity, cross-loadings, analysis of VIF, IPA, empirical correlation analysis, and bootstrapping analysis.

Principal Component Analysis

The application of principal component analysis in this research was, in the end, finding underlying patterns in a set of data to reduce its dimensionality and increase interpretability and usability as a consequence. PCA is particularly useful in transforming the original variables into a new set of variables, called principal components, which are made to be orthogonal to each other and absorb most of the variance existing in the original dataset.

Prior to performing PCA, the adequacy of data for factor analysis was done by using the KMO and Bartlett's Test of Sphericity. The sampling adequacy was appropriate for the variables, with a KMO measure greater than or equal to 0.6; that is, it shows that the proportion of variance in the variables which might be caused by underlying factors would be satisfyingly high. Bartlett's Test of Sphericity measures the suitability of the data being subjected to factor analysis [42]. If the p-value is less than 0.05, the test would indicate it to be significant, signifying enough correlation between the variables to perform factor analysis.

Principal component extraction was the first step in the PCA process. The criterion for retaining the components was kept as those principal components having eigenvalues greater than 1, ensuring that every retained component explains a reasonable amount of variance. A varimax rotation was performed on these components to render them interpretable. In simple terms, this is an orthogonal rotation, which tries to simplify the loading structure so that the output is more understandable and easier to interpret.

Component loadings were considered to check that variables loaded strongly onto their respective components, with loadings greater than 0.5 being significant [43]. This is an important step in the process of factor analysis as it validates that variables grouped under the same principal component are meaningfully related. The results from PCA gave many insights into the most critical factors and how the complexity reduction of the dataset could be achieved by maintaining the relevant information within the dataset.

By applying PCA, the study identified major constructs that explained most of the variance in the data. Because of this, it was analyzed much more directly and effectively. This not only simplified the dataset but also gave a more accurate subsequent analysis, which adds to a more robust and reliable finding.

4. Findings and Analysis

Demographic Details

This research was conducted in Saudi Arabia. A total of 182 respondents have participated in this research, as shown in Table 3. The gender distribution was very dominantly male, with 120 (65.9%) of them being male respondents and 62 (34.1%) female respondents. In terms of age categorization, participants fell into five categories: 35 (19.2%) were aged 18-25 years, 70 (38.5%) were aged 26-35 years, 50 (27.5%) were aged 36-45 years, 20 (11.0%) were aged 46-55 years, and 7 (3.8%) were aged 56 years and above. On educational background, 20 (11.0%) respondents had a high school certificate, 80 (44.0%) were holders of a bachelor's degree, 50 (27.5%) had a master's degree, 25 (13.7%) were doctorate holders, and 7 (3.8%) held other educational qualifications.

Table 3 Demographics of the respondents.

Category	Subcategory	Number of Respondents	Percentage
Gender	Male	120	65.9%
Gender	Female	62	34.1%
Age	18-25 years	35	19.2%
Age	26-35 years	70	38.5%
Age	36-45 years	50	27.5%
Age	46-55 years	20	11.0%
Age	56 years and above	7	3.8%
Educational Background	High School	20	11.0%
Educational Background	Bachelor's Degree	80	44.0%
Educational Background	Master's Degree	50	27.5%
Educational Background	Doctorate	25	13.7%

Educational Background	Other	7	3.8%

Principal Component Analysis

Table 4 reflects the analysis of convergent validity and reliability for the four constructs: Inventory Management Optimization (IMOP), Logistics & Transportation Optimization (LTOP), Real-Time Demand Forecasting (RTDF), and Supplier Selection & Relationship Management (SSRM). The indicators measure the construct; factor loadings by each indicator represent the respective indicators. The measurement reliability of each construct is assessed using the value of Cronbach's Alpha (CA) and Composite Reliability (CR), and the convergent validity is tested through Average Variance Extracted (AVE). An IMOP construct with five indicators, IMOP-1 to IMOP-5, have their respective strong loadings: CA reaches 0.798, CR reaches 0.861, and AVE reaches 0.554. The LTOP construct has four indicators (LTOP-1 to LTOP-4) that have high loadings with a CA of 0.777, CR of 0.858, and AVE of 0.607. The RTDF construct has four high-loading indicators (RTDF-1 to RTDF-5) with a CA of 0.863, CR of 0.907, and AVE of 0.709. The SSRM construct comprises three high-loading indicators (SSRM-3 to SSRM-5) with a CA of 0.736, CR of 0.85, and AVE of 0.655. These values suggest that good convergent validity and reliability are possessed by the constructs [44].

Table 4 Path loadings with Reliability and Validity analysis.

Variables	Inventory Management Optimization	Logistics & Transportation Optimization	Real-Time Demand Forecasting	Supplier Selection & Relationship Management	CA	CR	AVE
IMOP-1	0.728	-	-	-	0.798	0.861	0.554
IMOP-2	0.767	-	-	-	-	-	-
IMOP-3	0.751	-	-	-	-	-	-
IMOP-4	0.766	-	-	-	-	-	-
IMOP-5	0.706	-	-	-	-	-	-
LTOP-1	-	0.845	-	-	0.777	0.858	0.607
LTOP-2	-	0.836	-	-	-	-	-
LTOP-3	-	0.598	-	-	-	-	-
LTOP-4	-	0.81	-	-	-	-	-
RTDF-1	-	-	0.873	-	0.863	0.907	0.709
RTDF-2	-	-	0.824	-	-	-	-
RTDF-3	-	-	0.817	-	-	-	-
RTDF-5	-	-	0.852	-	-	-	-
SSRM-3	-	-	-	0.79	0.736	0.85	0.655
SSRM-4	-	-	-	0.853	-	-	-
SSRM-5	-	-	-	0.783	-	-	-

The Heterotrait-Monotrait (HTMT) ratio is an evaluation of discriminant validity, which examines the ratio of the between-trait correlations to the within-trait correlations is shown in Table 5. In the case of this research, the HTMT values between constructs for Inventory Management Optimization, Logistics & Transportation Optimization, Real-Time Demand Forecasting, and Supplier Selection & Relationship Management lie below the 0.90 threshold, representing good discriminant validity. For this, the HTMT values need to be found for each pair of constructs. The HTMT value between Inventory Management Optimization and Logistics & Transportation Optimization is 0.319, between Inventory

Management Optimization and Real-Time Demand Forecasting is 0.509, and between Inventory Management Optimization and Supplier Selection & Relationship Management is 0.254. These values reveal that the constructs are differing and not the same concept.

The Fornell-Larcker criterion is the second approach to estimating discriminant validity. It assumes that the square root of the AVE for all constructs should be greater than the highest correlation with another construct shown in Table 5. In this research, the square root of AVE is 0.744 for Inventory Management Optimization, 0.779 for Logistics & Transportation Optimization, 0.842 for Real-Time Demand Forecasting, and 0.809 for Supplier Selection & Relationship Management. The square roots of the AVEs for all constructs are higher than the respective correlations between the constructs, which indicates that there is sufficient discriminant validity among the constructs. For example, the correlation between Inventory Management Optimization and Logistics & Transportation Optimization is 0.244, which is less than its AVE square root of 0.744.

The cross-loadings are tested to check that each indicator loads more to its intended construct than to any other constructs, thus confirming the discriminant validity shown in Table 5. As evidenced in this research, the indicators under each one of the constructs show higher loadings on their constructs relative to the other constructs. For instance, IMOP-1 has a loading of 0.728 on Inventory Management Optimization versus its loadings on Logistics & Transportation Optimization, which are 0.163; Real-Time Demand Forecasting, which is 0.21, and Supplier Selection & Relationship Management at 0.109. Similarly, the loading of LTOP-1 on Logistics and Transportation Optimization is very high at 0.845 compared to 0.133 of Inventory Management Optimization, 0.28 of Real-Time Demand Forecasting, and 0.171 of Supplier Selection & Relationship Management. This result fulfills the stipulation that every indicator should have a higher association with its own construct than with others for the model to exhibit discriminant validity.

Table 5 Discriminant validity analysis.

Constructs	Inventory Management Optimization	Logistics & Transportation Optimization	Real-Time Demand Forecasting	Supplier Selection & Relationship Management
Inventory Management Optimization	-	-	-	-
Logistics & Transportation Optimization	0.319	-	-	-
Real-Time Demand Forecasting	0.509	0.499	-	-
Supplier Selection & Relationship Management	0.254	0.257	0.216	-
Constructs	Inventory Management Optimization	Logistics & Transportation Optimization	Real-Time Demand Forecasting	Supplier Selection & Relationship Management
Inventory Management Optimization	0.744	-	-	-
Logistics & Transportation Optimization	0.244	0.779	-	-
Real-Time Demand Forecasting	0.424	0.403	0.842	-
Supplier Selection &	0.133	0.195	0.172	0.809

Relationship Management				
Variables	Inventory Management Optimization	Logistics & Transportation Optimization	Real-Time Demand Forecasting	Supplier Selection & Relationship Management
IMOP-1	0.728	0.163	0.21	0.109
IMOP-2	0.767	0.272	0.325	0.097
IMOP-3	0.751	0.173	0.271	0.105
IMOP-4	0.766	0.103	0.445	0.064
IMOP-5	0.706	0.195	0.322	0.121
LTOP-1	0.133	0.845	0.28	0.171
LTOP-2	0.175	0.836	0.295	0.109
LTOP-3	0.229	0.598	0.315	0.133
LTOP-4	0.242	0.81	0.379	0.195
RTDF-1	0.407	0.369	0.873	0.261
RTDF-2	0.306	0.318	0.824	0.084
RTDF-3	0.35	0.271	0.817	0.076
RTDF-5	0.363	0.395	0.852	0.151
SSRM-3	-0.076	0.09	0.172	0.79
SSRM-4	0.167	0.217	0.073	0.853
SSRM-5	0.227	0.162	0.179	0.783

The figure 1 illustrates the factor loadings and path coefficients for the different constructs of Neuromorphic Optimization in Construction Supply Chain Logistics: Real-Time Demand Forecasting, Inventory Management Optimization, Logistics & Transportation Optimization, and Supplier Selection & Relationship Management. Each respective construct has a representation in terms of its indicators: RTDF-1 to RTDF-5, IMOP-1 to IMOP-5, LTOP-1 to LTOP-4, and SSRM-3 to SSRM-5. The loadings of these indicators are shown by values over 0.7, which means a very high association with the construct. In addition, the diagram shows the path coefficients between constructs as well: for example, 0.477 (from Inventory Management Optimization to Neuromorphic Optimization) and 0.430 (from Logistics & Transportation Optimization to Neuromorphic Optimization), at $p < 0.05$ [45]. Strong, significant relationships are shown among constructs in the validation of models' ability to explain how these elements result in optimal logistics of the construction supply chain using neuromorphic approaches.

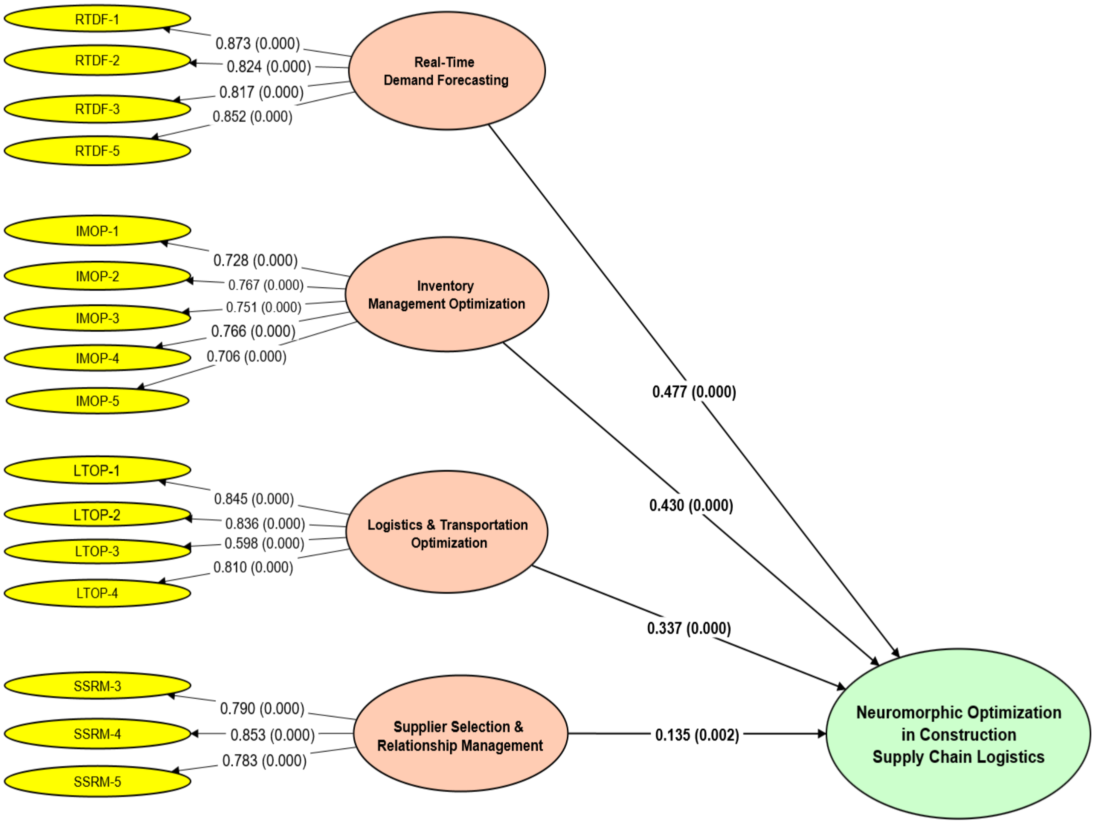

Figure 1 Structural Model with path loadings and P value.

The empirical correlation analysis presented in the heatmap shows the relationships between various indicators within the constructs of Inventory Management Optimization (IMOP), Logistics & Transportation Optimization (LTOP), Real-Time Demand Forecasting (RTDF), and Supplier Selection & Relationship Management (SSRM) shown in Figure 2. The heatmap displays correlation coefficients, with values ranging from -1 to 1, indicating the strength and direction of the relationships. Darker red signifies high positive correlations, while shades of blue stand for lower correlations. For instance, the indicators of each construct, such as those from IMOP-1 up to IMOP-5, have highly correlated positive indicators, showing internal consistency. The same case applies to the indicators for RTDF, which have a very high inter-correlation in this construct. Weaker correlations among different constructs, such as those of IMOP and SSRM, on the other hand, indicate that these constructs are quite distinct from each other. The presented CFA analysis showed good internal coherence of the constructs and confirmed the validity of the measurement model.

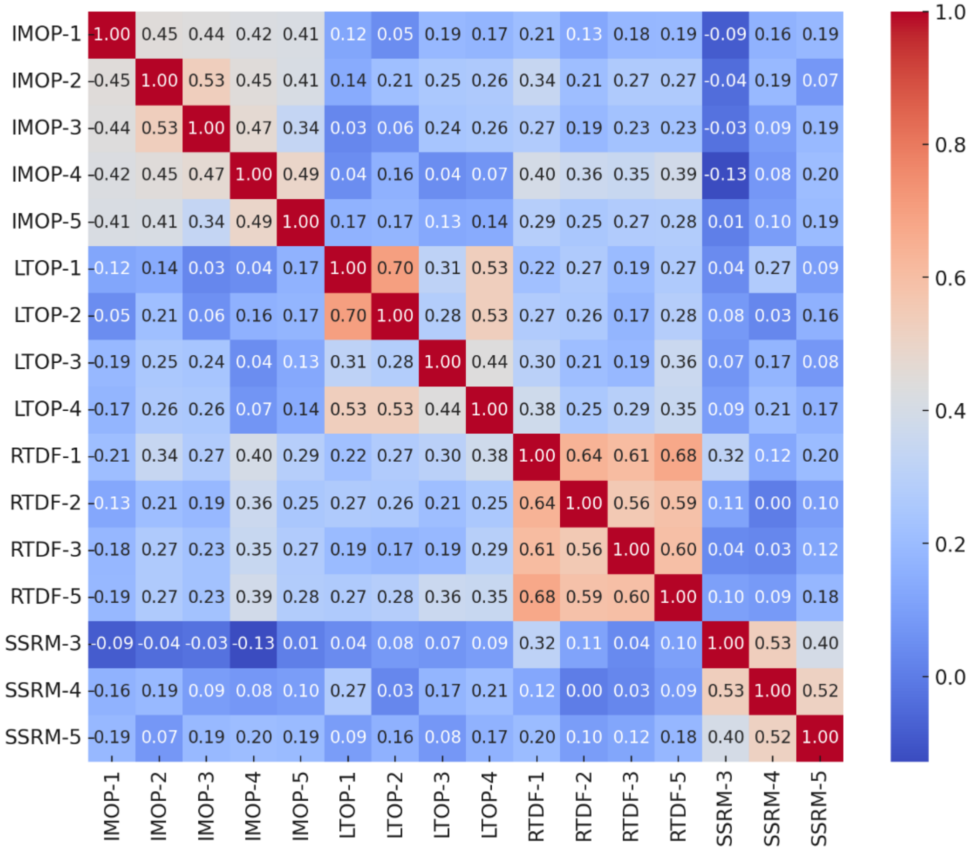

Figure 2 Emprical correlation analysis.

Table 6 summarizes the Variance Inflation Factor, total effects, and performance scores for the indicators in four constructs: Inventory Management Optimization, Logistics & Transportation Optimization, Real-Time Demand Forecasting, and Supplier Selection & Relationship Management. All the VIF values are less than 5, providing assurance against problems of multicollinearity and suggesting that the predictors are unrelated to each other.

For Inventory Management Optimization, the VIF of IMOP-1 and IMOP-2 are 1.463 and 1.62, respectively; the total effect is 0.43, with a performance score of 53.209. Logistics & Transportation Optimization has LTOP-1 at a VIF value of 2.143, with a total effect value of 0.337 and a performance score of 56.063. Real-Time Demand Forecasting includes RTDF-1 (VIF = 2.367) having an overall effect of 0.477 and a performance score of 45.035. Supplier Selection & Relationship Management has SSRM-3 (VIF = 1.429) with an overall effect of 0.135 and top in performance with a score of 62.425. The results aligned with previous study [46].

These values indicate the relative importance and effectiveness of each indicator within their respective constructs, which underlie the constructs' strong performance in the context of neuromorphic optimization in construction supply chain logistics.

Table 6 VIF indications along with Impact Performance analysis.

Constructs	Variables	VIF	Total Effects	Performances
Inventory Management Optimization	IMOP-1	1.463	0.43	53.209
	IMOP-2	1.62		
	IMOP-3	1.603		
	IMOP-4	1.611		
	IMOP-5	1.465		
Logistics & Transportation Optimization	LTOP-1	2.143	0.337	56.063
	LTOP-2	2.126		
	LTOP-3	1.252		
	LTOP-4	1.676		
Real-Time Demand Forecasting	RTDF-1	2.367	0.477	45.035
	RTDF-2	1.908		
	RTDF-3	1.848		
	RTDF-5	2.143		
Supplier Selection & Relationship Management	SSRM-3	1.429	0.135	62.425
	SSRM-4	1.645		
	SSRM-5	1.407		

Table Hypothesis Testing Results: Hypothesized Impacts of 4 Constructs – Inventory Management Optimization, Logistics & Transportation Optimization, Real-Time Demand Forecasting, and Supplier Selection & Relationship Management – on Neuromorphic Optimization in Construction Supply Chain Logistics. Each of the below hypotheses has been tested by evaluating the path coefficient (O), Mean (M), Standard Deviation (SD), t-statistics (T stats), and p-values [47].

With a t-statistic for Inventory Management Optimization of 10.17, the p-value is equal to 0, and the path coefficient is equal to 0.43, showing a positive impact on neuromorphic optimization. Similarly, Logistics & Transportation Optimization has a significant positive impact, with a path coefficient of 0.337 and a t-statistic of 8.857, and a p-value of 0. Real-Time Demand Forecasting has the highest path coefficient, 0.477, a t-statistic of 12.511, and a p-value of 0, being quite statistically significant and positively strong. Finally, Supplier Selection & Relationship Management has a path coefficient of 0.135, a t-statistic of 3.041, and a p-value of 0.002, signalling significance but with less of a positive impact in proportion. These findings pointed to the critical importance of all four constructs in enhancing neuromorphic optimization within the supply chain logistics for construction, of which the most influential factor was real-time demand forecasting.

Table 7 Hypothesis testing of neuromorphic computing factors.

Hypothesis	(O)	(M)	SD	T stats	P values
Inventory Management Optimization -> Neuromorphic Optimization in Construction Supply Chain Logistics	0.43	0.428	0.042	10.17	0
Logistics & Transportation Optimization -> Neuromorphic Optimization in Construction Supply Chain Logistics	0.337	0.332	0.038	8.857	0
Real-Time Demand Forecasting -> Neuromorphic Optimization in Construction Supply Chain Logistics	0.477	0.478	0.038	12.511	0
Supplier Selection & Relationship Management -> Neuromorphic Optimization in Construction Supply Chain Logistics	0.135	0.133	0.044	3.041	0.002

5. Discussion

The findings of this research demonstrated the important role that neuromorphic computing can play in optimizing supply chain logistics within the construction industry. The empirical results show that each of the four constructs, namely Inventory Management Optimization, Logistics & Transportation Optimization, Real-time Demand Forecasting, and Supplier Selection & Relationship Management, is a significant driver of neuromorphic optimization, though to varying extents.

Regarding inventory management, neuromorphic optimization had a strong impact, with a high path coefficient of 0.43 and a t-statistic of 10.17. This highlights the importance of real-time data processing and the adaptive learning capacity of neuromorphic systems in maintaining optimal inventory levels, minimizing overstock and stock-out situations, and thereby reducing waste and storage costs. The substantial loadings of the indicators within this construct further confirm the robustness of neuromorphic systems in inventory management and also align with previous research [13].

Logistics & Transportation Optimization also showed a significant positive effect, with a path coefficient value of 0.337 and a t-statistic of 8.857. Neuromorphic systems can dynamically route and schedule logistics based on real-time data from various sources, such as traffic patterns and weather conditions, thus saving time and lowering transportation costs. The high VIF values for indicators within this construct confirm the importance of managing multicollinearity, ensuring the reliability of the findings [48].

The most significant construct turned out to be Real-Time Demand Forecasting, with the highest path coefficient of 0.477 and a t-statistic of 12.511. This indicates that predictive analytic capabilities driven by neuromorphic computing are key to accurately forecasting material and resource needs, enabling construction companies to better plan and avoid delays and cost overruns. Real-time adaptation scored high performance in efficiency, with very significant indicator loadings in forecasting the demand of a supply chain [39].

Supplier Selection & Relationship Management had a lower but statistically significant impact, yielding a path coefficient value of 0.135 with a t-statistic of 3.041. The adaptive learning features of neuromorphic systems allow for an ongoing assessment of performance and optimization of supplier relationships to ensure qualitative and timely supply chain material fulfilment. Despite having a lower impact compared to the other constructs, it still emphasizes its importance in the overall functioning of the supply chain [49].

The entire model fitted the empirical data satisfactorily for the hypothesized relationships: all p-values were highly significant ($p < 0.05$), affirming the strength and validity of using neuromorphic computing in construction supply chain logistics. However, this research also identified potential challenges such as integrating neuromorphic systems into existing infrastructure, developing robust algorithms, and ensuring data privacy and security [50]. These challenges can be best addressed through further research and practical implementations, maximizing the benefits of neuromorphic optimization in the construction industry.

In summary, adopting neuromorphic computing in construction supply chain logistics will significantly improve efficiency, cost reduction, and project outcomes. Proven benefits in inventory management, logistics optimization, improved demand forecasting, and supplier relationship management highlight the transformative potential of neuromorphic systems in addressing the construction industry's complex and dynamic challenges.

Empirical and Managerial Implications

The results of this research demonstrate the potential for neuromorphic computing as a transformative technology in the logistics of the construction supply chain. Neuromorphic systems significantly enhance inventory management, logistics optimization, transportation optimization, demand forecasting, and supplier relationship management. These capabilities lead to increased efficiency, cost reduction, and overall project performance improvement.

For managers, practical applications of neuromorphic computing offer a robust framework for addressing traditional inefficiencies and complexities in supply chain logistics. Construction firms can use neuromorphic technologies to achieve better control over inventories, optimize logistics operations, and dynamically manage suppliers, resulting in significant cost savings, timely project completion, and improved resource utilization. This research provides a strong justification for integrating neuromorphic systems into construction supply chain practices and urges construction managers to adopt these advanced technologies to stay competitive and enhance operational performance.

Limitations and Future Directions

Although this research presents promising insights into the application of neuromorphic computing in construction supply chain logistics, it has several limitations. Integrating neuromorphic systems into existing infrastructure is resource-intensive, requiring significant investment in technology and training. Additionally, the development of robust and adaptable neuromorphic algorithms tailored to specific construction logistics needs remains an ongoing challenge. Data privacy and security issues are also significant concerns, given the sensitive nature of construction project data.

Future research should focus on developing standardized integration frameworks, advancing neuromorphic algorithm capabilities, and ensuring robust data security measures. Moreover, empirical studies involving larger sample sizes and diverse geographical locations would provide more comprehensive insights into the global applicability of neuromorphic computing in construction supply chain logistics. Addressing these limitations is crucial for fully harnessing the potential of neuromorphic technologies and driving innovation in the construction industry.

6. Conclusion

In essence, this research reveals the tremendous benefits of using neuromorphic computing to optimize supply chain logistics in construction. Optimization of inventory management, logistics and transportation, real-time demand forecasting, supplier selection and relationship management is done through neuromorphic systems, mimicking human brain neural architecture. There is concrete evidence that they bring many efficiency improvements and reduce costs, enhancing project outcomes. The most impactful was the Real-Time Demand Forecasting, which stresses dynamic and accurate forecasting concerning supply chain operations. Despite difficulties like integration issues with current infrastructures, algorithm designing, and data security, this research has drawn attention to the tremendous power of neuromorphic computing. Addressing these challenges through ongoing research and practical applications is very important for realising neuromorphic optimization in construction supply chain logistics, which will pave the way to a more responsive and efficient industry.

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