AIOT-BASED MULTI-SENSING STRUCTURAL DAMAGE ASSESSMENT FOR MODULAR INTEGRATED CONSTRUCTION (MIC) MODULES DURING TRANSPORTATION AND ASSEMBLY

HUSNAIN ARSHAD

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AIoT-based Multi-Sensing Structural Damage Assessment for Modular Integrated Construction (MiC) Modules During Transportation and Assembly

Husnain Arshad

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CERTIFICATE OF ORIGINALITY

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Signed _____________

Husnain Arshad

DEDICATION

I dedicate this thesis to God the Almighty, my parents, and my wife, Beenish Bakhtawar.

Abstract

Modular integrated construction (MiC) is widely adopted by industry and governments. However, its fragile and delicate logistics are still a concern for impeding project performance. MiC logistic operations involve rigorous multimode transportation, loading-unloading, and stacking during storage. Such rigorous logistics may cause intrinsic damage to the module, leading to a safety hazard and structural deterioration during building use. Meanwhile, the inevitable supply chain uncertainties add to the complexities, challenging the just-in-time (JIT) assembly goal. Therefore, continuous monitoring of the module structure during MiC logistics and the building use phase is vital. Consequently, the objectives of this research are to (1) investigate critical factors influencing MiC logistic operations, (2) explore technologies for addressing the challenges of MiC logistic operations, (3) develop a real-time sensing system for monitoring the MiC Module, and (4) develop a deep learning model for the MiC module's damage assessment.

To achieve first objective, the factors influencing the MiC supply chain and logistics are investigated through systematic review, eigenvector ranking, and MICMAC analysis. The second objective explores potential supply chain technologies and their benefits for MiC logistics using an NVIVO text analytics approach. Then, the synergies between the technologies' benefits and MiC challenges are discussed to enlighten the most beneficial technologies for MiC logistics. For the third objective, a multi-sensing IoT device is designed and developed to monitor the module's structure. The developed device is calibrated and tested to ensure accuracy. Application of the developed sensing device is also demonstrated for the MiC module's damage and safety monitoring through a detailed field experiment. A hybrid deep learning model is developed for damage assessment in the fourth objective. The model's architecture integrates the convolutional and sequential deep learning models. Model testing and validation are performed using a damage assessment scenario from the MiC field experiment.

The analysis of the influencing factors revealed critical factors, their interrelationships, and the themes demonstrating the factors' influencing mechanisms. Results also highlight prevalent factors affecting the MiC supply chain and potential factors that need further research attention. The synergy analysis between technologies highlighted the most beneficial technologies and the least addressed MiC challenges. BIM, RFID, and Blockchain are widely used but still lack applications to support several other MiC challenges. One such challenge is ensuring modules' structural safety and damage monitoring during transportation and assembly.

A multi-sensing IoT device has been developed to deal with the critical issue of real-time monitoring of the module structure. A compact and portable sensing device is designed to ensure its practicality for MiC modules while integrating an accelerometer, gyroscope, and strain sensors. Temperature calibration is performed using regression models to improve its accuracy. The device's performance prevails over the standardized commercial equipment, with less than a 5% difference. The application of the developed multi-sensing systems is successfully demonstrated for damage assessment on MiC modules using conventional methods, such as moving window analysis, FFT, strain histograms, etc. However, these analyses involve data pre-processing, excessive calculations, and the lack of capabilities for automated real-time assessment. The developed hybrid CNN-GRU deep learning model ensures the real-time automated damage assessment, having an accuracy (R^2) of 96%, with negligible mean square error. The deep learning model prediction led to accurate damage level assessment and localization for damage case scenarios.

Overall, this research theoretically contributes to the MiC, logistics supply chain, A-IoT sensors, and structural damage monitoring knowledge domains by (1) identifying the most critical influencing factors, their interrelationships, and mechanisms to influence the MiC supply chain; (2) identifying the most useful technologies for MiC logistics and highlighting the technology gap for addressing the MiC challenges; (3) integrating multiple structural response measurement sensors and wireless communication systems and establishing a robust IoT communication framework for the large data real-time transmissions; (4) evaluating the conventional damage assessment methods performance for the case of non-stationary MiC logistic operations; and (5) developing a hybrid damage prediction model architecture by integrating the convolutional and sequential deep learning models. Meanwhile, the study also offers practical contributions to the construction industry in the form of (1) a framework of critical MiC supply chain factors for improving the policies and logistic strategies, (2) identifying the most beneficial technologies available for improving MiC operations, (3) enabling the real-time module structural monitoring using the developed IoT sensing system, and (4) robust, automated damage prediction with the developed hybrid deep learning model.

Keywords: Modular Integrated Construction (MiC), Supply Chain, A-IoT sensors, Deep Learning

PUBLICATIONS ARISING FROM THE THESIS

Below is a list of research publications that the author of this thesis contributed to during this Ph.D. study, and as shown within the text, some parts of the thesis have been fully or partially published, with due acknowledgment, in these publications.

1. Arshad, H., & Zayed, T. (2022). Critical influencing factors of supply chain management for modular integrated construction. *Automation in construction*, *144*, 104612. DOI:10.1016/j.autcon.2022.104612

2. Arshad, H., & Zayed, T. (2024). A Multi-Sensing IoT System for MiC Module Monitoring during Logistics and Operation Phases. *Sensors*, *24*(15), 4900. DOI: 10.3390/s24154900

3. Arshad, H., Zayed, T., Bakhtawar, B., Chen, A., & Li, H. (2024), A Hybrid Deep Learning Model for Damage Predictions in MiC Modules During Transportation and Assembly, *Automation in construction,* (Under review)

4. Arshad, H., Zayed, T., Ahmad , T., Chen, A., & Li, H. (2024), Technological Interventions for Modular Integrated Construction (MiC) Logistics Supply Chain, *Automation in construction,* (Under review)

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Chapter 1

INTRODUCTION

1.1 Background

Modular integrated construction (MiC) is an offsite construction method where free-standing standardized buildings are manufactured in the factory and transported to the site for assembly. The buildings are manufactured as independent, standalone structural units called modules. The utilities, such as water pipes, fire safety systems and other fixtures, are pre-installed in these standalone building modules. Such fully equipped modules are assembled on-site to build an instant and fully functional building. Such a split construction approach shifts most construction activities into a controlled factory environment. The controlled factory operations enable automation, enhance sustainability, enable proactive value management, improve design precisions and built quality, and reduce labour demand [147]. Such technological improvements offered by modularisation can substantially boost the construction industry's productivity.

By shifting most activities to the factory, the assembly process becomes streamlined, enabling continuous assembly and ensuring faster building completion. Such reduced on-site construction activities substantially reduce the nuisance around the construction site, such as noise and dust, and relieve the people living around. Similarly, the reduced on-site logistic activities cause fewer obstacles and roadblocks. Such advantages are highly crucial for metropolitan cities, having congested spaces. Additionally, labour shortages are a significant concern for regions with increasing construction demand, such as Hong Kong, the USA, and the UK. Adopting MiC can reduce labour demand significantly, adding to its desirability as an innovative and automated construction method.

A recent study in Hong Kong reported several cost, time and sustainability-related advantages of MiC. A 25% time and 6-7% cost, 70% water & electricity reduction, and 100% productivity increase were observed for manufacturing and assembly-related operations [134]. Such benefits encourage the increasing adoption of the MiC approach. However, despite the encouraging benefits of MiC, the overall project performance and sustainability are challenged by various supply chain operations-related barriers, such as cross-border transit, transportation restrictions on module dimensions, storage limitations, and congested assembling sites [133]. Meanwhile, the complex MiC supply chain is prone to high uncertainties, risking its success.

1.1.1 MiC Supply Chain

It is a common misapprehension that advanced manufacturing technologies and simple on-site assembly activities make MiC project delivery less prone to systemic uncertainties. Yet, the MiC supply chain operations are complex and may cause delays in on-site module delivery, hampering the assembling rate [194,195,334]. MiC is a multimode, multi-tier, cross-border supply chain consisting of several fragmented segments, functioning independently and operated by different stakeholders [42,89,133], as shown in Figure 1-1. For example, a manufactured module is first transported to the shipping port on trucks, then after shipping arrives at the destination port, the module may need temporary storage before trucks transport them to the assembly site. All such supply chain segments may involve separate operators and stakeholders with conflicting goals and interests [359].

In such a situation, several other factors add to the complexity of its operations, such as (a) strict geometrical and dimensional constraints for transportation, (b) uncertain storage requirements, (c) cross-border transition, and (d) uncertain module flow across these fragmented but interconnected supply chain segments [148,360,375]. MiC is uniquely characterized by an ambidextrous module flow, where the assembling site controls module flow demand while the module supply is being pushed from the manufacturing end. MiC SC requires a push-flow of modules to ensure undisrupted site assembling operations. At the same time, a strict assembling sequence requires the demand-based pull-flow of the modules [137].

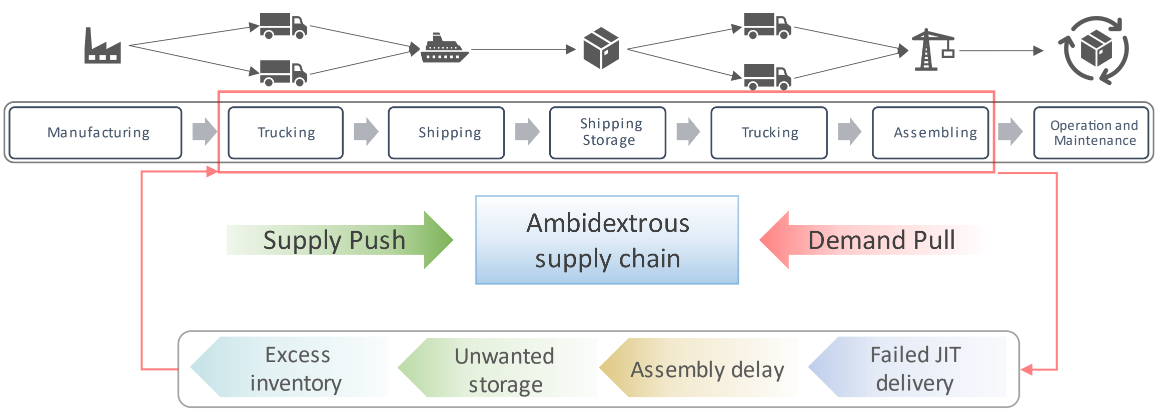


Figure 1-1. MiC supply chains' ambidextrous charaacomplexities

Meanwhile, MiC projects mostly follow a traditional hierarchical, restricted scheduling strategy with limited flexibility and inheriting systematic risks [42]. For example, the absence of on-site module storage adds to the need for just-in-time (JIT) delivery of modules [148]. For such an ambidextrous SC, the rate of assembling is critical, and site delays are inevitable [194]. Any assembling delay would create a snowballing effect for the whole supply chain, such as unwanted on-site accumulation of modules causing poor site space management and extensive accumulated inventories, causing excessive storage costs [359], as illustrated in Figure 1-1. Such supply chain disruptions are also evident in some recent cases in Hong Kong [194,195]. Therefore, MiC SC complexities demand a deeper understanding of its dynamics and the system of factors influencing its SC operational performance [147].

1.1.2 MiC Logistics Operations

Considering the module flow across complex MiC supply chain segments and snowballing disruptions under any uncertainty, the most critical point in the MiC supply chain is the on-site delivery of the MiC module before the assembly process. This point in the MiC supply chain inherits the least buffer space and flexibility in logistic operations, owing to the adoption of JIT assembly. The JIT assembly acquires the assembly processes to start as soon as the module arrives at the site to avoid additional module storage facilities and well manage the limited on-site space. Meanwhile, strict pre-assembly activities are conducted after the module's on-site arrival. Such as (a) untying and unloading from the truck, (b) conducting detailed inspections to check for its condition and potential damage, and (c) completing the repair work if needed.

In such a situation, if a module is severely damaged and needs extensive repair work, it will take an unwanted additional time, disrupting the JIT assembly. Consequently, it will cause snowball disruption in the whole supply chain, leading to on-site accumulation of arriving modules and the need for additional storage. In the worst case, a module may have damages beyond repair. Such a module might need to be replaced or repaired in the factory, causing cost overruns. Meanwhile, such a situation may also disrupt the module assembly sequence and stop the assembly process for longer.

Moreover, the pre-assembly module inspection is mainly based on manual methods and may sometimes involve measurement instruments to check for alignment [295]. Usually, a site inspector annotates measurements and observations on a checklist to verify any defects [242]. Such inspection is time-consuming and insufficient for a thorough module assessment to ensure safety and accurate alignment. The undetected damages may lead to severe impacts during assembly and later during the building use phase, as illustrated in Figure 1-2. A damaged module may delay the assembly process while fixing the misaligned and unlevelled surfaces. Also, hidden damage beneath the surface may propagate into major cracks and leakages, compromising the structural durability and affecting the module's serviceability. A plausible critical situation could be the module's structural failure during the building use phase. Therefore, the module's safe delivery is the most critical logistic operation for MiC [276,315].

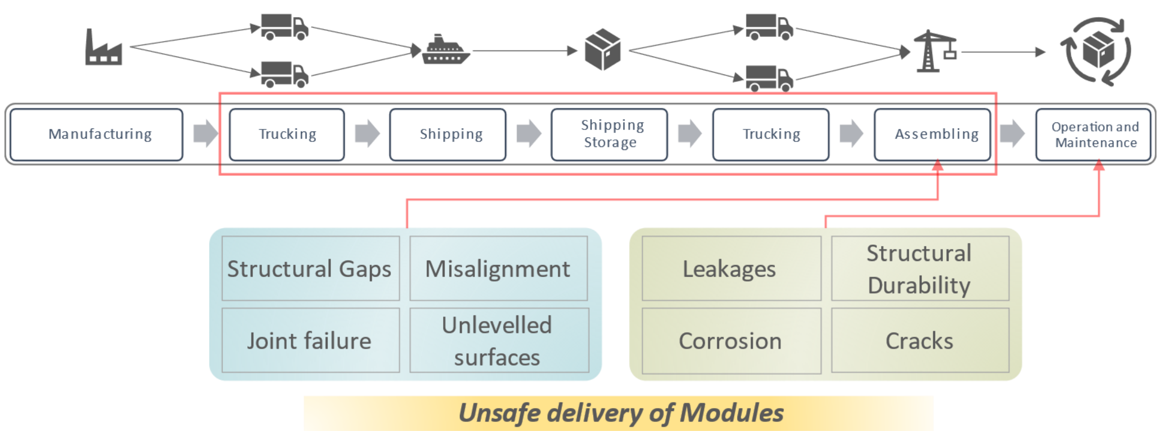


Figure 1-2. Module unsafe delivery and its potential impacts

A module is highly prone to damage during its logistics and supply chain operations, which involve (a) rigorous transportation, (b) recurrent loading-unloading, and (c) stacking during shipping and storage. Such operations expose module structure to various undetermined loads and impacts, such as (a) vibrations, shocks, and wind force during transport, (b) strains during crane lifting, and (c) uneven pressures during storage stacking [111,276].

Splittgerber [286] and Smith, et al. [276] reported that the structure loaded on a truck could be damaged if vibration exceeds three mm/s or acceleration exceeds 32 m/s^2. Such critical logistics operations seek proper investigation and suitable solutions. However, the damage does not only occur due to vertical acceleration; horizontal shocks due to instant breaking and road roughness may also cause a severe impact on the module. Similarly, the impact in the form of strain due to stacking of the module during storage and loading-unloading operations can also cause damage to the module. Such damage causes misalignment of modules for assembly, causing further delays while repairing such issues. Therefore, early damage detection is critical for the safety and long-term performance of the structure.

1.1.3 Real-time Module Monitoring During Supply Chain Operations

A damaged module causes a snowball disruption in the whole supply chain while affecting the module assembly process. Early damage detection can avoid such supply chain disruptions and manage the delay losses by (a) enabling proactive decision-making, (b) allowing early alternate arrangements, (c) early module return and saving resources, (d) ensuring the module flow, and (e) ensuring safety during module handling.

However, the MiC logistic operations are highly dynamic. Monitoring such a dynamic non-stationary structure is challenging, where both the structure and the impacting loads are moving [80]. The most existing technologies and methods for damage and structural health monitoring (SHM) are designed for traditional stationary structures [328]. The structure of a traditionally constructed building is mostly monolithic, where structural response at any location on the building can be sensed or estimated from any other location apart. However, in the case of MiC, the building comprises separate building blocks (modules), where damage in one module cannot be detected from any other module, as they are not joined monolithically. Therefore, several sensors must be installed on each module individually to monitor each module's structural response and performance.

Considering the above-discussed criticality of MiC logistics and the limitations of existing sensing systems, there is a dire need to develop an integrated, multi-sensing device to continuously monitor the module's structural response throughout its logistic operations and the building use phase.

Multi-sensing monitoring requires a robust integrated analysis for a holistic logistic impact analysis and a damage scenario evaluation. With the advancements in big data analytics and computing capabilities, multi-sensor data fusion and consequent damage assessment can be performed using deep learning tools [143,369]. Convolutional models are among the most powerful deep learning tools for effectively capturing spatial features from several sensor signals [219,303]. However, convolutional models can only extract the features in one dimension and learn the correlations among the sensors at each time instance. The sensor data consists of a time series of structural responses. For damage detection, the sequence of structural response in the time dimension is as important as the correlation among different sensors [47]. The variation in the sensor data across the time sequence provides important information about the change in the structural condition. Thus, temporal dependencies must be incorporated into the model for effective damage assessment.

Another type of deep learning model, sequential models, exclusively learns across the temporal dimension of the data [260]. These models maintain hidden states across time steps, capture sequential patterns, and thus model the sensor data dependencies across the temporal sequences. Owing to the exclusive capabilities of convolutional and sequential models, researchers have applied hybrid combinations of these to achieve better performance [72,366]. The existing studies using such methods for damage assessment are related to either bridges for traffic loads or traditional building structures for typical dead loads. The case of monitoring the MiC module structures is substantially different from such cases due to its moving structure during the transportation and assembly process. The previous research lacks any study that explores the structural damage monitoring and assessment of modular structures under the dynamic loadings caused by logistic operations.

1.2 Problem Statement

The modular integrated construction (MiC) has unique attributes related to its logistic operations. The existing studies rarely discuss the complex multi-tier, multimode supply chain and fragile logistics operations. However, the JIT supply chain demand for MiC assembly makes it vital to explore the dynamics of the MiC supply chain and logistics. So that critical influencing factors are identified and bottleneck issues are highlighted. Meanwhile, the latest construction industry, 5.0, demands technological solutions for enhanced performance and automation. Thus, exploring suitable technologies that effectively address the MiC logistics challenges is necessary.

The preliminary review and discussion above highlight that one of the vital challenges in MiC logistic operations is the damage occurring during module transportation and handling, which requires continuous real-time monitoring of the MiC module’s structure during logistic operations. Such monitoring requires a wireless multi-sensing system to sense the structural variations and communicate effectively in real time. The existing technologies are unsuitable for such MiC module monitoring and recognize its need.

Meanwhile, the existing data-driven methods for damage analysis and assessment are insufficient to handle the multi-sensor, non-stationary time-series data of the MiC module during logistic operations. Therefore, there is a dire need to develop a robust hybrid deep learning-based model development to enable the damage assessment of MiC modules.

1.3 Research Objectives

In light of the above discussion and literature gaps, the main aim of this research is to explore the dynamics and technological solutions for the MiC logistic challenges. To achieve this goal, the following objectives are determined.

I. To explore the factors influencing MiC logistics SC operations.

This objective explores the factors that influence the MiC supply chain, ranks those factors to identify the critical ones, investigates the interrelationships among the critical influencing factors, and consequently determines the influencing mechanism of these factors.

II. To explore the potential technologies for MiC logistics and synergies among technologies' benefits and MiC challenges.

The second objective investigates (1) the key challenges of MiC logistics, (2) the most suitable technologies for MiC logistics, and (3) synergies among MiC challenges and benefits for identifying the technology gap.

III. To develop a Multi-Sensing IoT system for monitoring the MiC module structure during logistics operations.

In the third objective, the multiple sensors and wireless communication components are integrated to develop a multi-sensing IoT device for monitoring the MiC module structure. The developed device is tested and calibrated to ensure its performance. A detailed application of the developed system is demonstrated for the MiC logistics.

IV. To develop a hybrid deep learning data-driven model for damage assessment in MiC modules.

This objective integrates the sequential and convolutional deep learning models to develop a hybrid model for MiC module damage prediction. The model is trained, tested, and validated from MiC logistic operations detailed field experiments.

1.4 Research Significance

The research aims to contribute to the MiC logistics and supply chain knowledge domains by investigating the factors and their influencing mechanisms on MiC logistics operations. Highlighting the technologies that address the MiC issues and identified technology gaps will enlighten the research directions. Decision-makers can benefit from the identified framework of critical MiC supply chain factors to improve policies and logistic strategies. Also, considering the determined synergies, the practitioners can rationally adopt suitable technologies for their relevant situations.

The integration of multiple structural response measurement sensors and wireless communication components allows robust and effective real-time module structural monitoring. The developed multi-sensing IoT system enables the decision-maker to monitor the module structure in real time and make timely decisions to avoid supply chain disruptions. The architecture of the hybrid damage prediction model adopts a novel approach to integrate the convolutional and sequential deep learning models to combine their exclusive capabilities. Such a hybrid model enables automated damage prediction and localization, which can further improve supply chain decision-making.

1.5 Overall Methodology

The overall methodological framework of this study is presented in Figure 1-3. For objective I, multiple research domains are explored to identify the influencing factors of MiC SC operations. Then, the significance of the identified factors is evaluated based on their potential influencing relationships, and the resulting themes are discussed.

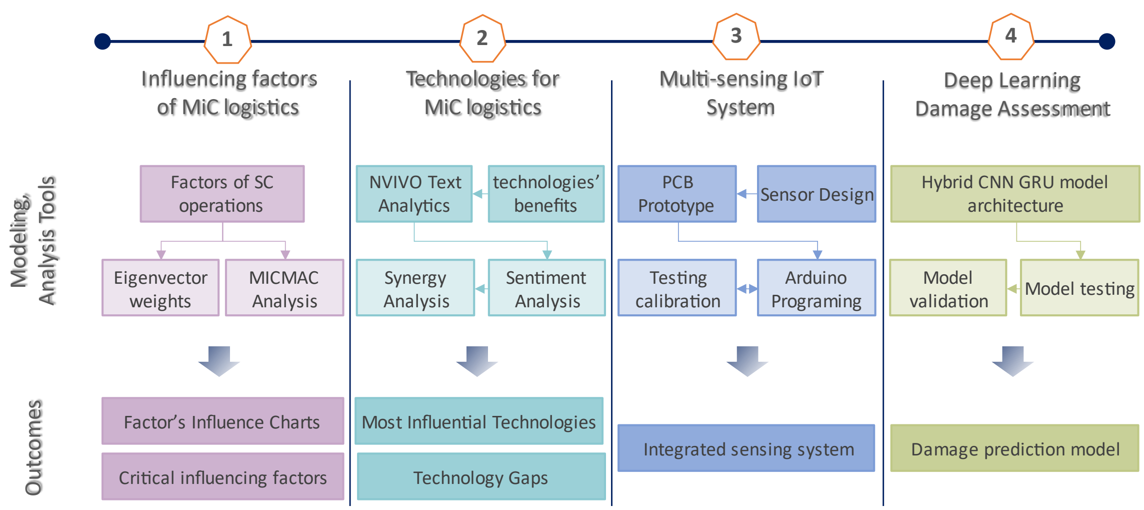


Figure 1-3. Overall methodological framework

For objective II, we first explored the unique challenges of the MiC logistics and SC operations. Then, the application of technologies in general SC, logistics SC, and construction SC areas is explored to identify the possible technological solutions for the MiC. An IoT-based sensing tool for real-time module monitoring during logistics operations is developed for objective III. The developed system is then thoroughly tested, and its application is demonstrated. Finally, in objective IV, a hybrid deep learning model architecture is designed to assess and predict the damage in the module. For this purpose, we evaluated different deep learning models to compare their performance.

1.6 Thesis Structure

This study contains a total of five chapters. After the introduction chapter, the detailed literature review is discussed for each objective in Chapter 2. Chapter 3 elaborates on each objective's methodologies, and the objectives' results are discussed in Chapter 4. Finally, the conclusions and future research plan for the remaining research are given in Chapter 5.

Chapter 2

LITERATURE REVIEW

2.1 Overview

In the first step, a preliminary review was performed to find the relevant studies within the MiC research domain. Table 2-1 summarizes the existing articles on the MiC supply chain-related factors. These studies offer a good understanding of the benefits and challenges of MiC adoption and implementation by identifying the relevant critical success factors [3,100], factors for sustainable design and assembly [147], and MiC project risks [138,335]. One of the recent studies explores the sustainable supply chain aspects of MiC. However, the study only uses bibliometrics and modelling techniques to analyze supply chain issues over MiC project life [147]. Other review studies examine the risks and critical success factors (CSFs) of supply chain management in MiC [89,335].

However, MiC supply chain operations dynamics have not been studied before, leaving a critical knowledge gap. Table 2-2 lists all the studies that mention MiC-related logistic issues. The focus of most of these studies is on scheduling and logistics planning, such as sequence for storage and stacking [42] and assembly schedule optimization [128,347]. Similarly, Lee, et al. [175] discuss the issues related to sequencing and stacking prefabricated panels. Some studies briefly discussed the impact of transportation on prefabricated structures [111,151,276]. One most recent study used the acceleration data to analyse the damage in module during transportation.

Table 2-1. Summary of studies focusing on MiC Supply chain factors

Article	Topic	Research Focus
Hussein and Zayed [148]	JIT.	Explores the success factors for implementing the JIT principle in the MiC supply chain.
Hussein, et al. [147]	Modeling techniques	Performs the bibliometric and scientometrics review for modeling tools and techniques used in offsite construction
Masood, et al. [205]	Company performance	Identifies the factors affecting the performance of companies in prefabricated housing
Correia, et al. [66]	MiC adoption	Analyze the factors influencing the decision to implement offsite construction in Australia
Ekanayake, et al. [88]	MiC SC resilience	Identifies the capabilities or characteristics of an efficient MiC supply chain, such as, resourcefulness, flexibility, capacity, adaptability, etc.
Ekanayake, et al. [87]	MiC SC vulnerabilities	Explores the critical supply chain vulnerabilities in Hong Kong MiC projects focusing on economic, technological, procedural, organizational, and manufacturing vulnerabilities.
Wuni, et al. [335]	MiC Project Risks	Identified MiC project risks comprising stakeholder and supply chain risks, design and capabilities risks, financing risks, and regulatory risks.
Fauzi, et al. [100]	MiC adoption	Explore challenges for implementing an industrialized building system in Malaysia's construction industry from a manufacturer's perspective.
Abdullah and Nasir [3]	MiC adoption	Challenges to integrate the supply chain for the adoption of the industrialized building system in Malaysia
Asri, et al. [28]	JIT.	Identifies the success factors for JIT implementation in industrialized building system

Table 2-2. Summary of studies focusing on MiC Logistics

Study	Research Focus
Zhang, et al. [368]	Assessment of carbon emissions during logistics operations
Wu, et al. [329]	Blockchain framework for cross-border logistics of modules
Huang, et al. [145]	Factory location optimization
Yang, et al. [347]	Schedule optimization of logistic operations
He, et al. [128]	Schedule optimization of modular transportation and assembling
Yang, et al. [348]	Exploring uncertainties during modular logistic operations
Lee, et al. [175]	Exploring issues during storage and stacking of prefabricated panels
Tažiková and Struková [299]	Assessing the costs of logistics and transportation of modular construction
Bortolini, et al. [42]	Planning the logistic operation using BIM
Asri, et al. [29]	Exploring the application of Lean for modular supply chain
Innella, et al. [151]	Investigating the structural performance of modules during transportation
Godbole, et al. [111]	Investigating the impact of transportation on the module's structure
Smith, et al. [276]	Monitoring the impact of transportation on the module's structure
Valinejadshoubi, et al. [315]	Monitoring transportation-induced damages in wooden modular houses

Overall, the research within MiC has rarely discussed logistics and supply chain operations issues. Therefore, we reviewed the research areas beyond the MiC supply chain. Figure 2-1 shows the overall structure of this review chapter, where studies from multiple supply chain-related industries and structural health monitoring are reviewed to investigate the relevant knowledge.

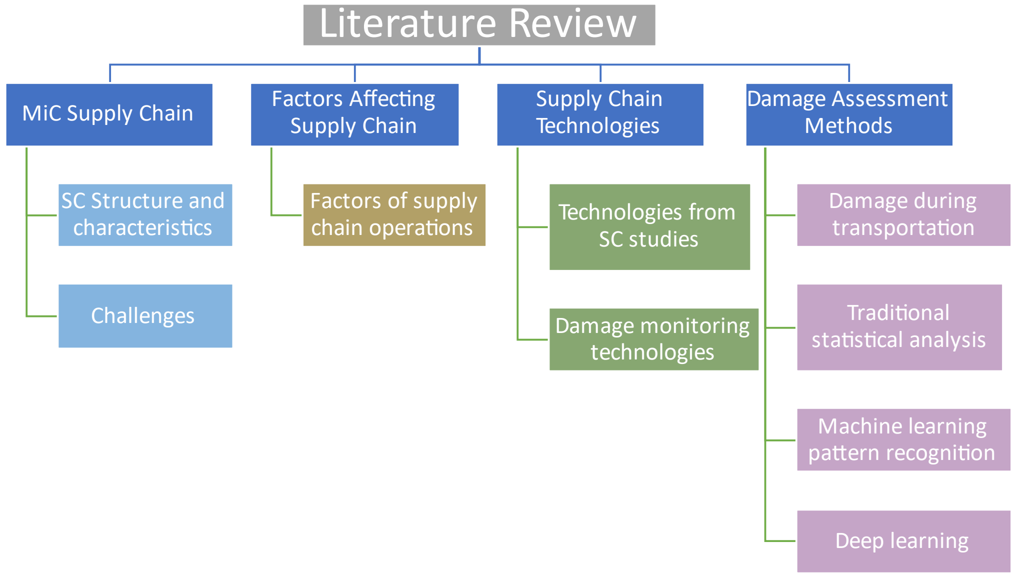


Figure 2-1. Overview of literature review

2.2 Challenges of MiC logistic supply chain

Logistics operations are the most critical aspect of a MiC project and, therefore, are considered a primary success criterion. Detailed logistic feasibility is performed at the early stage of the project to comprehend the challenges and their impacts. The MiC supply chain is complex and unique, requiring a multifaceted integration of several stakeholders' goals, information flow, and material flow across various independent supply chain segments [195,334]. Also, it involves complicated intrinsic challenges related to the logistic processes. This section provides insight into the challenges of the MiC logistic supply chain. For this purpose, research studies mainly focusing on the MiC and Hong Kong are reviewed, and critical challenges are identified in Table 2-3.

Table 2-3. MiC supply chain challenges

Challenges		References
Inventory Control	Overproduction	[137,194,232,331]
	JIT Production	[25,146,147,149,330,331,347,348]
Module Storage	Module handling	[25,194,334]
	Transit storage location	[133,334,348]
	Buffer space hedging	[194,195,330,332]
Transportation	Route and vehicle selection	[133,146,147,149,348]
	cross-border regulations	[194,375]
	local traffic management	[133,348]
	Travel uncertainties	[25,194,375]
Assembling delays	Delays due to equipment breakdown	[137,334,348,359]
	Delays due to bad weather and wind	[25,137,147,232,332,334,347,348,359]
	Delays due to transportation issues	[25,73,137,147,194,333,334,359]
	Delays due to wrong module delivery	[25,73,348]
	Delays due to installation errors and damage rework	[25,73,330,333,348,359]
	Resource wastage during recurring handling of modules	[133,348,359]
	Transportation and storage sequencing	[25,73,194,348]

Supply chain integration	Communication and coordination among stakeholders	[25,195,232,330,332-334]

2.2.1 Inventory control

Inventory management is critical to ensure the continuity of the processes. The planned extra inventory, called safety stock, plays a crucial role in meeting the uneven demand from the assembly site. On the other hand, the additional inventory stock is considered a non-value-adding activity as it causes extra storage costs [194]. Excess inventory is mainly caused by overproduction when the manufacturing rate is not synced with the assembly rate at the site. Such a demand-supply gap can be effectively managed at the planning stage by incorporating the demand uncertainties at the assembly site [137]. Ideally, the application of the just-in-time (JIT) principle can control the issue of excess inventory. However, applying pure JIT increases the risk of inventory shortage under uncertain circumstances and may affect the transportation process performed in batches. Therefore, Hussein and Zayed [149] proposed reducing the batch sizes and increasing the delivery frequencies. Moreover, inventory can be further controlled by improving the communication between site and logistics stakeholders [195].

2.2.2 Module Storage

The inventory management and storage needs are tightly linked with each other. Typically, the assembly site orders the modules from the factory 4-6 days before the scheduled installation, when the module is transported and delivered at a site [359]. Due to the short lead time, the factory manufactures the modules according to the master plan and stores them in factory storage until the site order is received. Also, modules are delivered to the site in batches, according to the floor assembly plan [194]. Luo, et al. [194] reported that the manufacturer started early production and stored initial inventory for 321 days.

Moreover, the overall average storage duration of the module was 44 days after assembling started. Such a long storage time causes high storage costs. Also, Wuni, et al. [334] and Luo, et al. [195] reported that module handling during storage cause severe wear and tear causing extra repair costs. The MiC module size and weight range between 3-8.68m long, 2-4.5m wide, and 7-13.5 tonnes [133]. The loading and unloading operations for such huge modules are critical, and excessive and frequent handling may cause damage to modules [334].

Further, modules are transported in batches according to the assembling cycle [359], which is 6-9 days [194]. Therefore, the delivered batch of modules must be stored on-site or at transit storage till the completion of each cycle [359]. Moreover, in case of delays in assembly, the storage time would be much longer. Luo, et al. [194] observed that the average on-site storage time (14 days) is much higher than the transit storage time (4 days). However, on-site storage is not possible in several cases due to a congested site layout or the absence of any nearby parking lot. In such cases, the location of transit storage becomes more crucial for optimizing the overall project costs. Some studies proposed enhancing the coordination between the logistic and assembling contractors by introducing shared profit and penalty mechanisms against saved storage time called buffer space hedging [361,362].

2.2.3 Transportation

The transportation for the MiC supply chain is characterized as multimode cross-border transportation. The challenges related to transportation involve the selection of transportation mode, choice of route, selection of vehicle/ship type, cross-border regulations, travel uncertainties, and traffic management [133,149,194,375]. The selection of route and mode of transportation depends on factors such as factory location, site location, size and weight of modules, batch size, road constraints, and border and traffic regulations [194]. Transportation by ship is considered more economical than other modes of transportation. Therefore, most MiC projects adopted transportation modes. For local road transportation in Hong Kong, vehicles carrying loads wider than 2.5m must apply for a Wide Load Permit (WLP) and a detailed Traffic Impact Assessment (TIA) study. Observing the local regulations, the MiC projects need to develop a detailed traffic management plan, and generally, a traffic consultant is also employed for efficient traffic management [133].

2.2.4 Assembling delays

The MiC assembly is considered the most critical part of the project, as delays in assembly affect the whole upstream supply chain, causing incurring costs [334]. Delays in the MiC assembling process are inevitable and cause schedule changes. Luo, et al. [194] reported that in the MiC project, assembling delays caused each assembling cycle to be delayed by an average of 3 days and the whole project delayed by 102 days. In the literature, late delivery of modules due to transport disruption is the most reported cause of assembling delays [73,137,194,334,359]. Some delay causes are related to the assembling process, such as a crane or other equipment breakdowns [334], and slow labor productivity due to unskilled or untrained workers [137]. Many delays are caused by damaged modules and installation errors, which require excessive repair work or replacement of modules [73,359]. Weather and wind are also the leading causes of delays or slow assembling [137,334,359]. In MiC projects, delivery of the wrong module or misplacement of the required module type is another significant cause of delay [73].

In MiC projects, buildings consist of multiple modules of different sizes and weights; up to 9 different types of modules are used for various MiC projects [133]. The variety of modules in a batch makes the logistic management processes more challenging. For example, different sizes and weights require a different vehicle for transportation or loaders for loading-unloading operations. In such a scenario, processes are prone to variance, which causes resource wastage [359].

Moreover, the identification of modules and record-keeping becomes crucial [194]. Typically, the record is manually maintained, which is prone to errors and may cause serious confusion in identifying the correct module. In such a scenario, the wrong module can be delivered at the site or maybe misplaced in a storage place; this would cause delays and resource wastage in finding the correct module [73]. Therefore, it is essential to maintain an efficient module identification system. Moreover, the logistic contractor must keep the module sequence during transportation and storage according to the assembly sequence. This way, there will be a lesser waste of resources and a lesser chance of mistakes in delivering the correct module at the site.

2.2.5 Supply chain integration

Generally, among other factors, supply chain integration is considered a key to an efficient logistic supply chain [334]. The MiC supply chain consists of several continuous segments that function independently, such as manufacturing, transportation, and site assembling. These segments are linked as a continuous flow of modules from one segment to another. In this case, any disturbance in the supply chain can halt the continuity of the whole supply chain. Uncertainty and disruptions are inevitable in the MiC supply chain and cause additional costs [137].

Moreover, multiple stakeholders are responsible for different supply chain segments, such as design and manufacturing contractors, third-party logistic contractors, and assembling contractors. In this case, a delay in assembly would cause the logistic contractor to hold extra stock of modules in storage, causing additional costs [194]. However, an integrated supply chain with effective coordination and communication among stakeholders can preemptively mitigate such issues.

2.3 Review of Influencing Factors for MiC SC

The influencing factors of the MiC supply chain were systematically reviewed. First, a preliminary search was conducted to (1) validate the research idea, (2) justify the need for this study, and (3) establish the precise research questions. Several queries were searched on Google Scholar and Scopus to find the relevant articles. The search queries consisted of several combinations of keywords and their variants related to the modular construction supply chain factors. As a result, ten modular construction review articles were found using these queries. Out of ten, only four review articles focused on the modular construction supply chain topic. Fauzi and Correia, et al. [66] focused on successfully adopting the modular construction supply chain. Whereas Hussein and Zayed [148] and Asri, et al. [28] focused on the implementation of the Just-in-time (JIT) approach for the modular construction supply chain. None of these review studies focused on studying the influencing factors of the modular supply chain. The preliminary search results substantiate this study's knowledge gap and research questions. Also, the existing review studies help provide a list of relevant keywords to develop a robust literature search design for systematic review.

2.3.1 Article search and screening

The performed systematic review adopts the methodology guidelines from Higgins, et al. [130]. The precise definition of inclusion and exclusion criteria is pivotal for a sound search design and reflects this study's objectives. The inclusion criteria are: (1) include studies related to the general supply chain management, logistics management, and modular construction supply chain; (2) include only those studies which contain influencing factors, such as critical factors, success factors, barriers, decision factors, risk factors, etc.; and (3) include studies from all the available years of publications, to avoid any temporal bias [130]. Similarly, the exclusion criteria are: (1) exclude studies from any specific industry or subject other than modular and prefabricated construction; (2) exclude studies that do not include any supply chain influencing factors; and (3) exclude inaccessible and non-English-language articles.

The general supply chain domain studies mostly focus on product flow management and coordination. These studies mainly discussed the management strategies such as sustainability, supply chain flexibility, Lean, TQM, etc. On the other hand, the studies from the logistics management domain mainly focus on collaboration among stakeholders and supply chain resource management, such as information flow, transportation management, storage location, etc. The construction domain contains all the studies related to modular construction and its similar supply chain, such as industrialized buildings, prefabricated or precast construction, volumetric construction, etc.

Scopus and Web of Science (WOS) databases were used to search for relevant studies. In the construction and supply chain domain, these databases are considered the most up-to-date and comprehensive [297]. An extensive search query was used to find articles from these databases. This query was developed considering the pre-defined inclusion and exclusion criteria (section 2.2.1). Further, the built-in database filters were applied to execute the exclusion criteria and remove irrelevant subject areas, such as medicines, chemicals, agriculture, arts, etc. As a result, we found 336 articles on Scopus and 248 from WOS. After removing the duplicates, the remaining 447 articles were further evaluated for eligibility.

A detailed evaluation and screening process is elaborated in Figure 2-2. In the first step, the duplicates were removed, and a title and abstract-based screening was performed using an inclusive approach. The articles focusing on generic supply chain management, logistics management, or various forms of modular construction were shortlisted. Studies related to other industrial applications, such as agriculture, petroleum, automobile, etc., were excluded. Following this, a full-text evaluation of the remaining (123) studies was performed. During the full-text review, the eligibility criteria were further reiterated by evaluating the nature of factors enlisted in these studies. Only those studies that fulfilled the pre-defined eligibility criteria were selected. As a result, a total of 66 relevant studies were found.

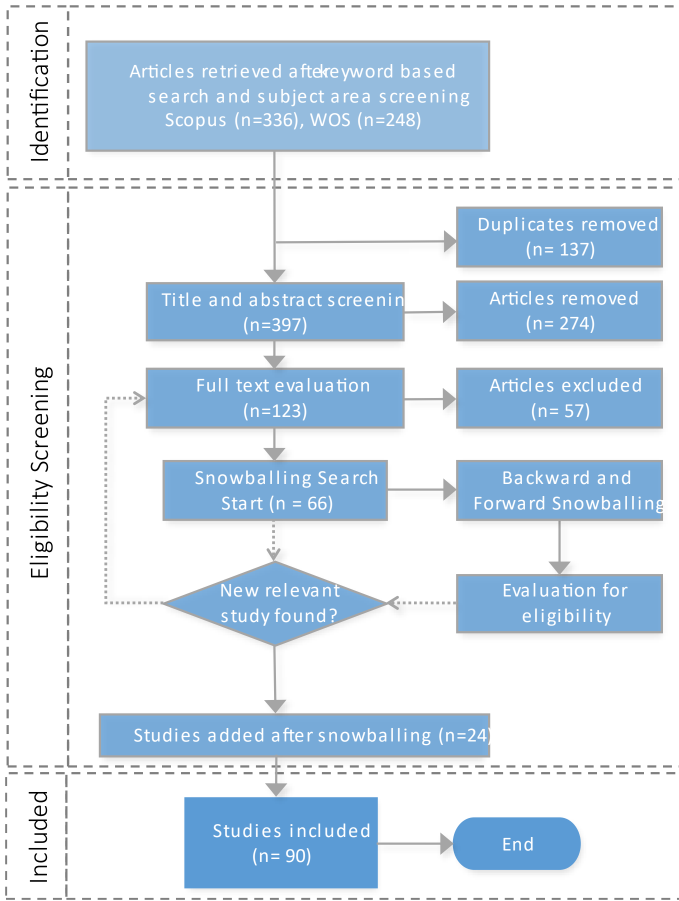


Figure 2-2. PRISMA flow diagram for screening of studies

Further, the forward- and backward-snowballing method was performed to extend the literature search. This snowballing helps reduce the database bias and overcome the keywords' limitations. The iterative snowballing process was conducted for every new study found until no new relevant study was found. As a result, 24 more articles were found and added to the final set of studies.

Initially, a total of 117 factors influencing the supply chain are found. Following the type of factors as well as their functional prominence, factors are categorized into four main groups: (1) Project management and strategic level factors, (2) Organizational factors, (3) SC operations-related factors, and (4) Product and design-related factors. The organizational and SC operations-related factors are the largest categories, with further sub-categories, as shown in Figure 2-3.

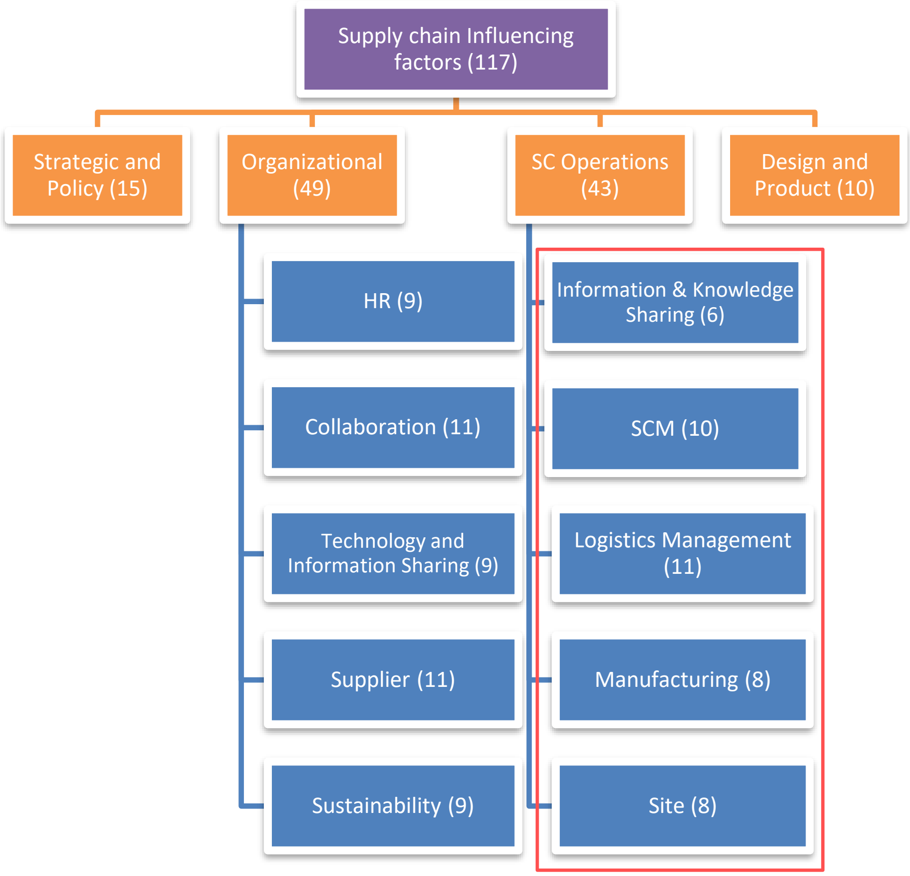


Figure 2-3. Overall supply chain factors and categories

2.3.2 Discussion on Influencing Factors of MiC Logistic Operations

This paper only focuses on the factors directly influencing SC operations. Therefore, only 43 SC operations-related factors are thoroughly investigated. SC operations-related factors are further categorized into five groups: 1) information & knowledge sharing (IKS), 2) supply chain management (SCM), 3) logistics (LOG), 4) manufacturing (M), and 5) site delivery (S). The detailed list of factors is presented in Table 2-4, and the factor's occurrence frequency is given in Appendix – B.

Table 2-4. List of factors influencing SC operations

Categories		Factors	Description
Information and knowledge sharing (IKS)	IKS1	Information technology tools	Adopt technology for effective communication and establish an integrated information management system.
	IKS2	Information flow SOPs	Adopting standardized procedures and guidelines for information technology use
	IKS3	Information transparency	Ensuring the transparency and clarity of information flow across the SC and among the members of the SC
	IKS4	Communication and knowledge Sharing with 3PL	Sharing up-to-date information with 3PL and sharing knowledge about the processes and modules
	IKS5	Efficient information flow	Establishing effective communication procedures and networks across the SC members
	IKS6	Real-time SC monitoring	Ensuring real-time information, trackability, and traceability of flowing processes
Logistics (LOG)	Log1	Module's handling	Damage to modules during loading, unloading, and transportation processes
	Log2	Flexible transportation	Multi-mode transportation and availability of alternate transportation routes
	Log3	Logistics delays	Delays due to weather and natural disasters
	Log4	Optimized transportation route	Designing optimized supply chain networks and Vehicle routing for multi-mode transportation
	Log5	Inventory control	Controlling rate of manufacturing and buffer space management at storage
	Log6	Logistics Cost	Cost of transportation, storage, and handling of modules, or cost of acquiring 3PL services
	Log7	Cycle time	Total time for module logistics operations from factory to site.

	Log8	Location and proximity of logistic facilities	Availability of facilities such as temporary storage, repair shops, labor, and alternate transportation facilities near the factory and along the transportation route
	Log9	Transportation regulations	Transportation and traffic restrictions for large trucks, Cross-border checkpoint regulations, Customs and excise procedures, and legal requirements.
	Log10	Standardization of logistic activities	Implementing SOPs for logistics activities and standardizing the processes. Implementing an integrated Logistics management system
	Log11	Green Transportation	Use of environmentally friendly transportation and distribution
Supply chain management (SCM)	SCM1	Robust SC	Adaptability, accessibility, swiftness, flexibility, and decisiveness
	SCM2	SC integration	Integration among all supply chain members
	SCM3	Management strategies	Adopt innovative management strategies: JIT, Lean, continuous improvement, and QMS.
	SCM4	Performance measurement	Implementing benchmarking and performance measurement system
	SCM5	SC monitoring	Controlling the operational performance through effective SC monitoring systems
	SCM6	planning and scheduling	Planning the SC elements, scheduling by employing comprehensive risk assessments, continuing monitoring to re-plan and re-schedule the activities
	SCM7	Decentralized decision-making	Decentralization of decision-making and distributed control across SC elements
	SCM8	Risk Management	Integration of risk management and SCM

	SCM9	Risk Sharing	Devising risk and reward-sharing mechanisms with SC members
	SCM10	Promoting sustainability	Practices to encourage sustainability and Energy conservation
Manufacturing (M)	M1	Material Flow	Material flow management, material handling, and quality control
	M2	Waste handling in the factory	Waste disposal and recycling at the manufacturing unit
	M3	Natural hazards	Delays due to natural factors such as weather and natural hazards
	M4	Worker's safety	Indoor environment quality and workers' health and safety
	M5	Green Manufacturing	Use of environmentally friendly materials and processes
	M6	Lead time	Planning manufacturing rate and schedule, managing lead time to control the inventory
	M7	Manufacturing Delays	Delays due to Equipment breakdown and labor disputes
	M8	Modules repairing	Manufacturing delays due to defects, reworks, design changes, and shortage of materials
Site delivery (S)	S1	Demand Variability	Dynamic variations in the assembling rate cause the variation in demand for modules at the site
	S2	Site Layout	Site layout and material flow management plan for efficient flow of materials
	S3	Communication at site	Passing Correct information for the required type of module for assembly/ following Spatial demand pattern
	S4	Delays due to weather	Delays due to weather and natural disasters

S5	Equipment breakdown	Delays due to equipment breakdown and labor disputes
S6	Delayed modules delivery	Delays in the delivery of modules to the site
S7	Worker's expertise	Labor productivity, contractors experience
S8	Assembling rework	Installation errors, complex rectifications, Variations/rework, utility disruptions, and reworks

2.3.2.1 Information and knowledge sharing factors (IKS)

The MiC supply chain is highly information-intensive. It involves several trades and stakeholders that generate and acquire information for effective operational performance. Such information includes module specifications, locations, inventory status, storage availability, site assembling status, etc. Therefore, *efficient information flow (IKS5)* is critical for an effective and robust SC [220]. It can help enhance SC resilience by reducing SC disruptions [88] and maintaining SC agility [256]. Thus, it is imperative to establish an effective information flow system across the supply chain and among different SC organizations [233,272]. Such an effective information system can be warranted by *real-time SC monitoring (IKS6)* [233,298]. For an ambidextrous SC, like MiC, r*eal-time SC monitoring* is indispensable [206]. It not only offers integration of supply chain segments but also ensures the smooth flow of modules [256,257].

Adopting *information technology tools (IKS1)* has been seen as an effective way to implement efficient and real-time information flow [199,241]. Such tools directly influence SC performance and help enhance organizational performance [169,193,217]. RFID is the most commonly adopted technology for real-time information flow [317]. As mentioned earlier, MiC SC requires an extensive information flow along with the module flow. Such information includes the identification and location of the module. The RFID and GPS technologies record all the module-related information and share it in real-time when enabled with a wireless gateway [320]. This real-time information flow facilitates module traceability and ensures the sequence of module flow. Thus, providing the module flow according to the assembling works at the site so that just-in-time (JIT) delivery can be guaranteed [148]. This way, *Information technology tools (IKS1)* also support enhancing sustainability in the supply chain by reducing the wastage of time and resources [59,140,169].

In a multi-stakeholder environment, *communication and knowledge sharing with 3PL (IKS4)* are essential to SC performance [304]. Effective communication among all SC organizations introduces SC resilience [238,271], responsiveness [271], integration [3], and flexibility [273] and also promotes sustainability [185,199]. Moreover, in an information-intensive MiC supply chain, loss and misuse of information could be a serious issue [89]. Therefore, ensuring *information transparency (IKS3)* is deemed essential for SC performance [109,283]. For this purpose, establishing *information flow SOPs (IKS2)* could be a practical element of SC performance [88,193,363]. Recently, blockchain technology has also been adopted to ensure information security, traceability, and reliability [342].

2.3.2.2 Logistics-related factors (Log)

The MiC logistics operations primarily include transportation, loading and unloading, and storage of modules. Considering the multi-mode cross-border transportation of MiC modules, *flexible transportation (Log2)* arrangements are critical [89]. In case of disruptions, an alternate transportation mode should be available in backup [88,255]. Moreover, the *optimized transportation route (Log4)* may not always be effective during module transportation [229]. Several critical external factors, such as *logistics delays (Log3),* might impose a change in transportation mode and route [334]. Further, the *transportation regulations (Log9)* primarily influence the decision to select the transportation mode and route [334,365]. Among other factors, the *location and proximity of logistic facilities (Log8)* play a crucial role in determining optimized transportation routes and overall SC performance [229]. Also, the factor *Log8* directly influences the *logistics cost (Log6)* [264] and *cycle time (Log7)* [246].

The *logistics cost (Log6)* [160] and the *cycle time (Log7)* [172,289] are directly influenced by *inventory control (Log5)*. It is one of the critical factors which can control the overall SC performance [148]. The optimum level of inventories may eliminate the need for storage [118] and hence reduce the *logistics cost (Log6)* and *cycle time (Log7)*. Further, the *module's handling (Log1)* is a delicate job. Any mishandling may cause damage to modules, and additional repair work will be needed at the assembling site [334]. Similarly, the loading and stacking arrangement is critical for modules and requires additional attention. The wrong stacking arrangement would disrupt the unloading sequence and may cause additional delays. To overcome such issues *standardization of logistic activities (Log10)* is recommended [13,148,271].

2.3.2.3 Supply Chain Management-related factors (SCM)

A *robust SC (SCM1)* is characterized by adaptability, accessibility, swiftness, flexibility, and decisiveness [88,271,273]. The primary function of these factors is to deal with the SC vulnerabilities and control the impact of disruptions [88]. Such SC capabilities are governed by several other SC operational factors [341]. Among those, *SC integration (SCM2)* helps to improve the SC flexibility and decisiveness, thus increasing the SC robustness [8,226]. On the other hand, *SC integration (SCM2)* enhances communication and coordination among several SC organizations [100,211]. Similarly, the factor *promoting sustainability (SCM10)* involves activities to implement strategies that improve sustainability practices, such as waste minimization [105], energy conservation [263], adopting recycling [140], etc. Such practices support improving the overall sustainability performance of SC.

Further, the implementation of *management strategies (SCM3)* such as just-in-time (JIT), lean and agile can potentially influence the SC robustness [28,148]. JIT and lean principles generally enhance SC accessibility, swiftness, and decisiveness [8,112], whereas the agile principle improves SC flexibility [243]. In a complex multi-stakeholder environment, decision-making could be tricky and have implications beyond the internal SC elements. In such a situation, the *decentralized decision-making (SCM7)* approach has been considered adequate [88,148]. This approach distributes the authority across the SC and empowers SC members to contribute to SC performance while focusing on mutual benefits. Further, to evaluate and administer the performance of SC members, *SC monitoring (SCM5)* and *performance measurement (SCM4)* are considered significant factors [8,294,304].

The implementation of project management approaches is found to be an influential factor in enhancing SC performance. For example, implementing a *risk-sharing (SCM9)* mechanism can effectively control the performance of SC members by sharing the rewards and decreasing the liabilities [271,272,316]. Also, meticulous *risk management (SCM8)* would support assessing, managing, and mitigating the SC vulnerabilities and risks [190,263]. Similarly, detailed *planning and scheduling (SCM6)* can successfully influence the overall execution of SC processes [2].

2.3.2.4 Manufacturing-related factors (M)

The *efficient material flow (M1)* inside the factory will lead to meeting the manufacturing targets and will reduce the *lead time (M6) [187]*. To ensure *efficient material flow (M1),* a detailed material management plan can help timely material acquisition and avoid delays [274]. The material management plan also focuses on *green manufacturing (M5)* for proper *waste handling in the factory (M2)* [351]. So that *workers' safety (M4) can be ensured by the* appropriate disposal of hazardous materials [2,326].

The *lead time (M6)* is one of the most critical factors directly influencing the SC flow. It can delay the on-time module manufacturing, thus delaying all subsequent segments of SC [30,229]. The *lead time (M6)* can be affected by *Natural hazards (M3)* such as rain, earthquake, etc. [283,334]. Similarly, manufacturing delays (M7) due to equipment malfunctioning and module repair (M8) can significantly increase *lead time (M6)* [326].

2.3.2.5 Site delivery-related factors (S)

The MiC module assembling process is highly dynamic and uncertain due to several critical factors, such as *delays due to weather (S4), equipment breakdown (S5), delayed modules delivery (S6), worker's expertise (S7), and assembling rework (S8).* The module assembling process involves crane lifting, which is highly sensitive to wind and rain conditions. In case of high wind or rain, the crane cannot operate and, therefore, would delay the assembling process [148]. Similarly, *equipment breakdown (S5)* will stop the assembly process. The assembly process involves the delicate work of aligning and fixing the module joints, which requires *workers' expertise* (S7) and sometimes needs rework to repair the joints correctly. In such a scenario, the assembling duration remains highly uncertain and unpredictable [335].

Such uncertain delays lead to *demand variability (S1)*, disrupting the whole supply chain, particularly transportation and storage in previous tiers. The *efficient site layout (S2)* and effective *communication at the site (S3)* can help deal with such issues. The *efficient site layout (S2)* may offer a larger working space to incorporate multiple machines or temporarily at the site. Thus, an *efficient site layout* can provide buffer space to absorb the impact of *demand variability (S1)* [326]. Similarly, real-time and effective *communication at the site (S3)* can improve the coordination among different trades to handle the assembling disruptions [30,229].

2.4 Review of Technologies for Logistics and Supply Chain

2.4.1 Article search and screening

The review aims to investigate the application of several technologies in the logistics and supply chain area. Therefore, a preliminary study was conducted to identify all the technologies in this area. During the initial investigation, relevant review articles in the last five years were searched using the keywords 'technology' and 'supply chain.' These review articles helped establish a detailed list of logistics and supply chain technologies. Then, an explicit search query was generated to search all the articles related to the application of technologies in logistics and supply chains published since 2010. The identified list of technologies was included in the keyword list of the search query. The query was performed on Scopus and Web of Science (WOS) databases. These two databases are considered sufficient for searching research articles because of their broader coverage, rapid indexing process, and access to recent publications compared to other databases [207].

The exclusion criteria for the search are defined to consider articles related to the different technologies in logistics and supply chains. Therefore, the search was limited to only engineering journals and articles on applying technologies in logistics and supply chains. Articles related to medicine, social science, aerospace, automobile, etc., were also excluded using the database filters. As a result, a total of 2,001 articles were identified. The article screening process is elaborated in Figure 2-4 using PRISMA flow.

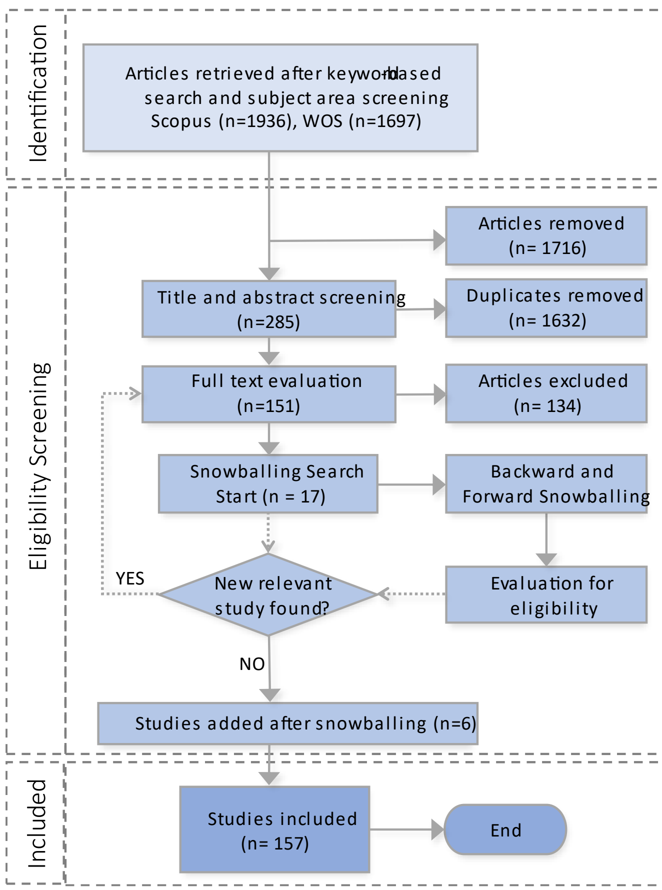


Figure 2-4 PRISMA flow chart for article selection and screening

Articles were further evaluated by reading their title and abstracts, and 285 articles were found relevant. These selected articles were thoroughly read and assessed against the inclusion criteria: (1) the article covers the application of technology for logistics or supply chain operations, and (2) it highlights the benefits obtained through this application. As a result of the inclusion criteria screening, we shortlisted 151 articles. Further forward, snowballing was also conducted to exhaust the possibility of overlooking relevant publications on the subject matter. As a result, 157 articles were finally found for further review and analysis.

2.4.2 Identified Supply Chain Technologies

The selected articles were thoroughly studied to extract information related to the application of technologies and their prescribed benefits. Of the selected studies, around 25% belong to the construction supply chain, and the remaining studies are from other supply chains, such as manufacturing, retail SC, food SC, etc. The overall publication trends of these studies are shown in Figure 2-5(a). It reveals that most of the included studies were published in the last five years. This indicated that the research focus in SC domains had been tilted toward technology application.

Surprisingly, blockchain technology has been widely studied in the supply chain despite a relatively new revelation. RFID and IoT have been studied for a long time but are comparatively less attracted by construction studies. BIM has been thoroughly implemented in construction studies and applied to other supply chain areas, such as manufacturing. The detailed application of these technologies is discussed in the following sections.

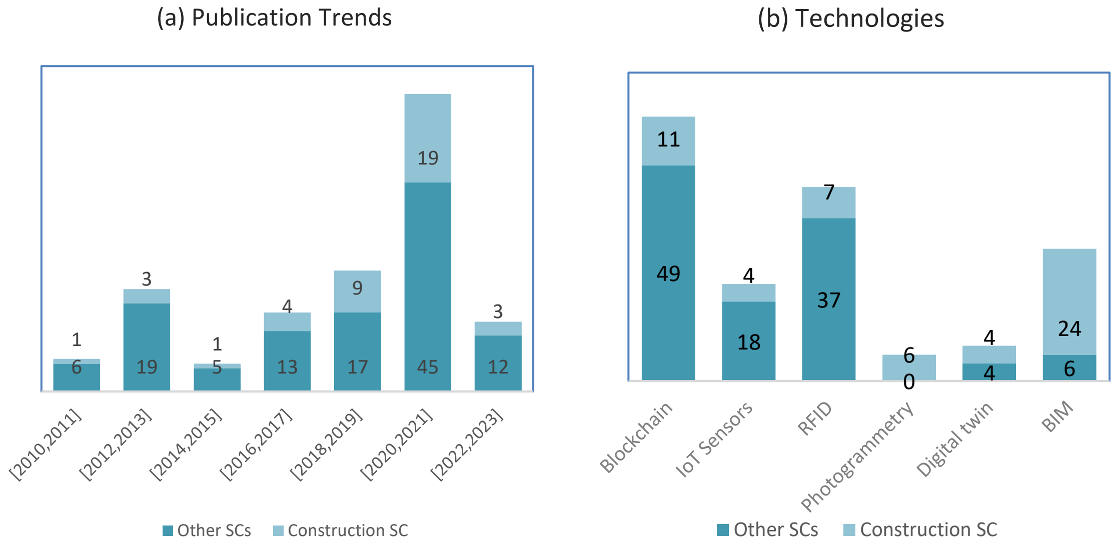


Figure 2-5. Scientometrics trends from reviewed articles

2.4.2.1 Blockchain and Smart Contracts

Blockchain is a distributed ledger technology that creates a continuously growing list of blocks or records [180]. These blocks of records are linked and secured using cryptography. Its decentralized and secure nature makes it ideal for conducting transactions between two parties without intermediaries [338]. The blocks are saved on several connected computers, each having a copy of the entire ledger, thus verifying the validity of every new transaction or block. The blockchain can also automatically execute its operations by following a pre-stored logical algorithm called smart contracts. Smart contracts allow automatic process execution when specific rules or conditions are met [161].

Such features of blockchain make it a transformative technology that provides a secure, transparent, and decentralized way of conducting transactions and storing data [338]. It can potentially reduce costs and resource wastage [70,161,203,321], increase efficiency, and improve trust and transparency between parties [7,176,180,203,339], making it a promising technology for various industries, such as finance management, supply chain management, and digital identity verification. Further details on the benefits of blockchain are listed in Table 2-5.

Table 2-5. Benefits of Blockchain

Blockchain Application and Benefits	References
Enhanced security, trust, pseudonymity, transparency, and data integrity	[7,70,176,180,203,313,321,338,339]
automated transaction generation, decentralized decision-making, and data storage	[176,180,338]
Reduced transaction costs, audit costs, paper costs, verification costs, networking costs, R&D costs, and contracting costs; removal of nonvalue-adding intermediaries	[7,70,161,203,321,339]
Direct and real-time access data sharing and collaboration with stakeholders	[161,176,180,222]
Effectively deterring fraudulent products and Identities.	[161]
trustworthy information management during all building lifecycle stages	[180,240,313,339]
traceability of construction project quality	[161,265,339,370,372]

In a blockchain, decisions are democratized and secured as transactions are performed through peer-to-peer endorsement and verification by a digital signature [338]. Thus, retail supply chains adopt blockchain for reliable delivery and to ensure error-free mass customization. It also significantly reduces operational costs in terms of transaction costs, audit costs, paper costs, verification costs, contracting costs, etc., [161]. For the same reasons, blockchain in construction projects is adopted to strengthen the traceability of materials across design and construction and ensure quality during the building maintenance and use phase [240,265,339,370,372]. It can also help manage the information, material flow, and project documentation, thus enhancing collaboration and enabling automated payment systems [168,180,313].

2.4.2.2 IoT and Sensors

The Internet of Things (IoT) is a network of physical devices, vehicles, buildings, and other objects embedded with sensors, software, and network connectivity, enabling them to collect and exchange data [65,353]. An IoT system comprises two parts: (a) sensors and devices and (b) wireless communication. Sensors and devices in an IoT system collect data from the environment around them, such as temperature or motion detectors. Sensors' collected data is sent to an online cloud and then communicated in real-time to the other person or devices through the internet using Wi-Fi or cellular networks after processing [323] [353]. IoT has been widely applied in the logistics SC to increase efficiency, safety, and security of warehouses, transportation, and delivery [164]. In retail SC, it solves food safety problems by offering more agile and convenient merchandise management [23,188]. IoT has also been applied in construction for several operations, such as IoT-based material control systems in manufacturing facilities [323]. The list of identified benefits of IoT and its embedded sensors is given in Table 2-6. The following sections further discuss the application of different sensors in SC.

Table 2-6 Benefits of IoT and its embedded sensors

IoT and Sensors Application and Benefits	References
<u>Internet of Things (IoT)</u>	
Increased efficiency in assembly systems	[323]
Increased efficiency, safety, and security of operations related to warehousing, transportation, and last-mile delivery	[164]

Agile and convenient management of merchandise	[188]
RFID and Barcodes	
Real-time tracking of workers for safety monitoring	[43,191,208]
Efficient warehouse operations	[17,85,300,319,340]
Detecting tampering and potential theft	[44,208]
Safety and security of merchandise	[44,208]
Tracking and traceability throughout the delivery process	[162,201,208,281]
Detecting damaged or spoiled products	[44,123,162,201,208,281]
Smart packaging, auto-checkout	[63,155,208]
Inventory control, real-time traceability of raw materials	[50,63,115,132,154,155,191,208,281,319,352] [282,323]
Reducing operating costs and waste	[63,155,191,208] [213,323]
Enabling just-in-time, lean, and agility	[45,52,77,126,144,213]
Enhanced logistics management	[60,82,191]
Improved quality control	[191,322]
Tracking the hidden parts or buried assets	[84,191]
Efficient human resource management	[85,191]
Heat and Temperature sensors	
Detect heat-stress conditions of construction workers.	[85,86]
Heat sensing in confined spaces to monitor health and safety	[27,85,121,174,248,314]
Food condition monitoring in containers	[354]
Global Positioning System (GPS)	

Material and equipment location tracking	[85] [21,85]
Measuring Labor activity	[85,156]
Automated monitoring of construction sites to avoid clashes and accidents among moving equipment	[85,227] [85,247]
Optimum vehicle routing for material delivery	[78]
Accelerometer	
Measuring vibrations experienced by prefabricated modules during transportation, ensuring safe transportation	[183]
Distance, Proximity sensor	
Handling the manufacturing, warehouse, and indoor transportation to avoid equipment or good clash	[230]

RFID and Barcodes

Radiofrequency Identification (RFID) and Barcodes are used for identifying and tracking objects, but they differ in their mechanisms and the types of information stored. Barcode technology uses manual scanning of the visual patterns, while RFID uses radio waves for automated data collection [45,312]. Thus, RFID can store relatively large amounts of data compared to a barcode. The RFID tag can store up to 128 kilobytes of data (passive RFID:256 bytes, active RFID: 128 kilobytes). An RFID reader can detect several tags simultaneously, from up to 25m distance, as it works with powerful waves with up to 5.875 GHz frequencies [208,323]. Such advantages enable better real-time information visibility and traceability [115,131,191,336].

On a construction site, RFID has diverse applications, such as maintaining the material inventory [77,132], materials identification [208,281], and distinguishing materials in dusty or muddy environments [191]. RFID further enhances the monitoring of work progress when combined with other civil-related management software, such as 4D CAD and BIM [60,191,322]. It can also help track the 3D location of buried assets [84,191], depth of piles, pipe spools, and other valued items on construction projects [82,191]. RFID also has significant applications in precast production management systems [191,352]. RFID has been used on construction sites to monitor the worker's and machinery's movements to enhance health and safety [85,191,300]. It can also monitor the construction demolition process for proper material waste management [191].

Heat and temperature sensors

Heat and temperature sensors measure the heat or temperature of an object or a particular environment. These sensors can detect heat or temperature variations in various applications, such as monitoring the temperature of machinery and food during storage or measuring the temperature of a particular environment. These sensors have been widely applied in retail supply chains to monitor food conditions during delivery [354]. Temperature sensors, along with light and humidity sensors, are also used to monitor the storage conditions of perishable goods [23,310].

In construction, heat sensors are applied to measure physical exertion and fatigue in workers involved in manual material handling jobs [27,121,174,314]. Wearable and e-textile technologies are developed to monitor workers' physiology and health in real-time [85,86]. Also, the environmental conditions in confined spaces are monitored using these sensors to enhance safety [85,248], such as for underground construction, mining, and tunneling projects.

Global Positioning System (GPS)

GPS and GIS are distinct yet related technologies typically used in various supply chain applications. GPS technology relying on satellite-based navigation is used to collect location data, which can then be integrated into GIS software to create maps and analyze geospatial data, such as tracking and monitoring the vehicle's location. This information can be used to optimize routes [78]. In construction, GPS data can help with the automated monitoring of construction equipment and determine risks on job sites to avoid collisions [85,227,247]. Similarly, the labor movement can be monitored to improve the worker's safety [85,156]. It has also been used with other technologies, such as RFID or barcodes, for material and equipment tracking to reduce construction waste [85]. It can also monitor the timely supply of resources to ensure seamless activities, such as the supply of precast components [21,85].

Accelerometers

An accelerometer is a sensor that measures the acceleration of an object, typically in three dimensions. Using acceleration data it determines the movement and orientation of the object. Accelerometers have been used in the construction supply chain to monitor the prefabricated components mounted on trucks [183]. Vibration and acceleration-related data from accelerometers can also help determine the fatigue experienced by construction workers [174,200].

Distance and proximity sensors

Distance and proximity sensors measure the distance or presence of a moving object. These sensors are commonly used in manufacturing industries, such as automotive, aerospace, and electronics. Several types of distance and proximity sensors are available, including ultrasonic, laser, infrared, and capacitive. Ultrasonic sensors are the most commonly used for monitoring indoor machinery movement and material handling, as they detect objects between 300 mm to 5000 mm distance, with an accuracy of 1mm. On the other hand, an infrared sensor more precisely detects between 40 mm and 300 mm and is, therefore, commonly used for construction machinery clash alerts [230].

2.4.2.3 Photogrammetry

The photogrammetry technique measures physical objects and environments using images. The process involves taking multiple photographs or images of an object or environment from different angles and using specialized software to analyze the images and generate accurate measurements. Its applications are wide-ranging, from creating 3D models of buildings and landscapes to mapping archaeological sites and developing comprehensive data for scientific research.

Photogrammetry has several applications in the construction supply chain, such as collecting images of a built environment and developing a BIM model [69]. BIM models generated through photogrammetry can identify defects in the constructed components [184]. Similarly, CCTV images of the project site can help monitor the real-time progress of the project schedule [10]. This way, photogrammetry can be used as a powerful management and decision tool by monitoring real-time progress and quickly responding to changes [184].

Table 2-7. Identified benefits and capabilities of photogrammetry tools in SC

Photogrammetry Application and Benefits	References
Photogrammetry	
Generate as-built information	[69]
Assessing the quality of production, improving lead time of responding to changes	[184]
Identification of defective prefabricated units	[184]
Generate BIM models of existing buildings.	[69]
Monitoring real-time progress of project schedule	[10]
Monitoring fatigue of construction workers	[174,200]
LIDAR, Laser scanning	
Generates as-built information about a building	[69]
Detecting and recording dimensions and smoothness of prefabricated products	[192]
Generate and record as-built information of a building in the BIM model identify differences in building execution from design.	[10]
Computer vision	
Monitor construction progress using 4D BIM, automate rule checking within BIM models, automate as-built 3D reconstruction using computer vision, monitor construction performance using still images.	[99,124,125,236,279,280,344]
Identify and distinguish construction materials and equipment	[85,293]

Laser scanning

Laser scanning helps measure objects' and surfaces' shape, size, and position in 3D space. It is used in several industries, including manufacturing, engineering, architecture, and construction, for various applications such as quality control, reverse engineering, building surveys, and modeling. The accuracy of laser scanning helps generate accurate and detailed 3D models or digital representations of objects. One of the benefits of laser scanning is its ability to capture data from complex and hard-to-reach areas, making it useful for applications such as inspecting pipelines or bridges [10]. It is also a non-destructive method of testing, which can be helpful when dealing with delicate or valuable objects [69]. Deep cameras and laser scanners in production plants are used to detect and record the dimensions and smoothness of prefabricated products to ensure quality [192].

Computer vision

Computer vision (CV) is the latest approach for analyzing images or photogrammetry data using artificial intelligence. CV aims to develop algorithms that automatically and accurately detect, recognize, and measure the features of an object from the imagery data. This technology is being used for several applications, such as autonomous vehicles, facial recognition, object detection, medical imaging, and surveillance. In the construction industry, computer vision is used to identify, distinguish, or measure the construction materials and equipment [85,293]. It is also being used to monitor the construction performance using still images [99,124,125,236,279,280,344].

2.4.2.4 Building Information Modeling (BIM)

Building Information Modeling (BIM) is a developing innovation that facilitates the creation and exchange of reliable and consistent data between various members of the construction supply chain. BIM enables the digital rendering of any structure, allowing for more efficient design, construction, and management throughout the structure's lifecycle. This digital model includes crucial information concerning the building's components, such as geometry, quantities, spatial relationships, and material properties. BIM enhances design coordination and promotes knowledge sharing among relevant stakeholders. Its built-in features, like clash detection visualization, scheduling, and control capabilities, improve construction operations [31,173]. It offers advantages not only in design management [90] but also in project management, resulting in reduced project time, enhanced communication and coordination [31], decreased costs, and fewer information returns [46,235].

Table 2-8. Identified benefits and capabilities of BIM and Digital Twin in SC

BIM and Digital Twin Application and Benefits in SC	References
Building Information Modeling (BIM)	
progress monitoring of construction projects, facility management	[85,216]
improved design coordination, knowledge sharing among relevant actors	[31,173]
visualization for clash detections, controlling and scheduling capabilities, facilitating construction operations	[31,173]
time reduction, better communication, improved coordination, lower project costs, reduced project information-related issues	[46,235]
enhancing performance of mechanical, engineering, and plumbing trades in construction projects	[9,173]
stronger SC partnerships, improving trust among SC actors	[173]
Digital Twin	
streamline and increase the productivity of production processes	[288] [183]
Identify shortcomings in systems.	[288]
monitoring construction resources and progress	[178,183]
occupational health and safety management	[159,183]
Enhanced facility management	[58,183]

BIM plays a catalytic role in supporting construction SC stakeholders for effective supply chain management in construction. Such as it improves trust among all stakeholders by enabling consistent and real-time information-sharing [173]. Integrating with other technologies, such as RFID, BIM adds value to the supply chain performance. For example, monitoring the progress, maintenance, and facility management [85,216]. The laser scanning approach can help record the as-built information of a building or building component into a BIM model where as-built information can be compared with original design information, and changes or defects can be identified [10].

2.4.2.5 Digital Twin

A digital twin is a digital model and a virtual replica of an object or process. It utilizes advanced technologies such as machine learning algorithms, the Internet of Things (IoT), and sensor data to simulate the behavior and characteristics of real-world objects or systems. Various industries, such as healthcare, manufacturing, and transportation, utilize digital twins to improve performance, optimize processes, and reduce costs. With the use of digital twins, real-time data can be monitored and analyzed to identify potential issues and simulate different scenarios for better decision-making.

In retail supply chain management, digital twins can be employed to optimize processes, streamline production, and identify production bottlenecks. By identifying potential system shortcomings, Digital Twins can help improve future change proposals before implementation [288]. For construction projects, integrating IoT data with BIM has become a fundamental approach in creating digital twin applications that enhance productivity [183]. These applications have been widely utilized for monitoring construction resources and progress [178,183], occupational health and safety management

[159,183], construction logistics and supply chain management [183,373], and facility management [58,183].

2.5 Sensing Technologies for Damage Monitoring

For structural health monitoring (SHM), numerical modeling is time-consuming and expensive, but it is still unreliable; for accurate modeling, precise data of each point on the structure and each damage scenario is required in advance. Therefore, structural response under a particular loading or force is measured to assess the effect on the structure. For this purpose, several sensing technologies are used to monitor the loadings and structural response. The vibration-based, strain-based, guided waves, and acoustic emissions technologies are most common for buildings and bridges SHM [120]. The table 2-9 below summarizes the commonly used sensors and features of each sensing technology.

Table 2-9. Commonly used technologies for SHM

Technology	Sensors	Features
Vibration-based	Accelerometers	Global range, limited resolution, sensitive to environmental conditions and disturbances
Strain-based	Foil Strain Gauge, Piezoelectric Sensors, FBG Sensors	Local range, limited resolution, high sensitivity, sensitivity to environmental conditions, accurate damage quantification,
Guided waves	Piezoelectric Sensors	Mid-range, high sensitivity, not suitable for thick composite materials, sensitive to noise
Acoustic emission	PZT acoustic wave sensors, AE probes	Mid-range, not suitable for thick composite materials, sensitive to noise

2.5.1 Vibration-based

The vibration method or modal analysis is usually used to improve finite element models (FEM) using experimental vibration data. These methods have limited resolution for structural damage detection, making them suitable only for identifying large cracks that significantly alter the first frequencies and modal shapes [117]. Also, the accuracy of this method is easily affected by environmental conditions, uncertainties, and measurement errors [75]. However, analyzing large data can certainly overcome such a limitation of accuracy and efficiently detect damage at the global structural level [113]. For acceleration data, modal strain energy and damping ratio are considered better damage indicators than natural frequencies [120].

2.5.2 Strain-based

The strain-based method measures the displacement that occurs at any point under loading. Several strain sensors are available for measuring the strain in the structural elements, such as resistive strain gauges, piezoelectric, and FBG sensors [120]. The main disadvantage of this method is that strain detection is only significant near the sensor position. Any strain away from the sensor will have little impact on the sensing [152]. The strain mapping approach has been used to deal with this issue. It detects changes in the strain field caused by the local loss of stiffness and subsequent strain redistribution and, hence, assesses the damage in a larger area [12].

2.5.3 Guided Waves

This method is more commonly used in aeronautics due to its potential to detect minor damage, which is critical for an aircraft. The common guided wave sensor is piezoelectric material in ultrasound transducers (PZT). When attached to the structure, the PZT sensor emits a short ultrasonic pulse of a few hundred kHz, propagating through the structure as an elastic wave, and is received by a secondary PZT sensor. Any signal distortion indicates a change in structure between two sensors. This technique effectively detects even minor damages in flat surfaces like cylindrical tubes. However, its application is challenging for thicker and condensed structures [12]. The waves change their characteristics (such as mode, shape, speed, etc.) in thick composite materials because of rigorous reflection or refraction at every interface [214].

2.5.4 Acoustic Emissions

In the acoustic emission method, an inaudible acoustic signal is released at one end of the structure's surface, and change in response is measured at the other end. This method captures elastic waves produced by growing cracks that liberate energy [209]. Therefore, it's more effective for detecting fatigue in structural elements. PZT acoustic wave sensors are commonly used for this method as they are smaller, less expensive than standard probes, and less sensitive [228]. The issues in this method are similar to the guided wave, such as wave reflection, distortion, and damping. However, guided waves actively release controlled signals of the same shape, whereas acoustic signals are short packages of frequency, intensity, and duration information. Therefore, there are different processing algorithms for both methods. Also, noise is more critical in acoustic emissions; hence, an additional preamplifier is installed near the sensor to eliminate noise and improve signal quality [120].

2.6 Damage Detection During Transportation and Handling

Early damage detection is critical for the long-term safety and performance of the structure. In prefabricated modules, the damage is initiated mainly during logistics operations, such as transportation and module handling [276]. Godbole, et al. [111] studied the acceleration impact on the module during transportation and found that vertical acceleration can reach up to 32 m/s^2 (3.3g). Therefore, the module design should be able to incorporate this impact. Alternatively, the vibration dampers could be installed below the module floor to dampen the truck-induced vibrations. However, the damage is not caused only by vertical acceleration; horizontal shocks due to instant breaking and road roughness may also cause a severe impact on the module. In addition, the impact in the form of strain can also damage the module components during its loading-unloading operations.

In this context, the MiC logistic operations cause a dynamic and non-stationary structural response that can be measured and analyzed to detect structural changes or damage. Several sensors are installed at different locations to monitor the MiC module structure. The most convenient and commonly used sensors for SHM are accelerometers that sense the acceleration or vibrations along all three axes. The statistical methods are used to analyze the accelerometer data for damage assessment. These methods follow the principle of structural response variation under similar loading conditions, causing vibrations in the structure. The existing damage assessment methods are mostly suitable for stationary data. These methods compare the two states of a structure (undamaged and damaged) by comparing the sensor response measured under static conditions. A non-stationary scenario contains high noise in the data, which is impossible to distinguish and remove from the sensor signal. Also, achieving similar loading or motion conditions during MiC logistic operations is highly unlikely.

Further, the module is exposed to several linear and rotational motions under logistic operations. Therefore, a gyroscope and an accelerometer are needed to capture the module's movement fully during logistic operations. Like an accelerometer, a gyroscope measures rotational motion along three axes: roll, pitch, and yaw. Although, the combination of acceleration and gyroscope can effectively capture the motion of the structure. However, it is still impossible to distinguish the variations in these sensor signals due to changes in structural conditions occurring during highly dynamic logistic operations. Once the damage occurs, the structural response measured by these sensors will show some variation but not significant enough to be distinguished, particularly in the presence of high amplitudes in the sensor signals caused by the logistic motions. Also, the inertia measuring sensors (accelerometer and gyroscope) are more suitable for measuring the variations in the structural response at the global level, and locating the damage position requires additional probabilistic assessment.

In this context, the strain gauge sensor can measure the structural deformation locally, more precisely, while directly indicating its position. The strain gauge sensors are attached to the structure and measure the structural deformation based on the change in the flowing current levels. When there is any significant change in the structural condition due to damage, the affixed strain sensor shows a substantial change in the flowing current, indicating that damage. However, the strain sensor measured response is highly local and can only accurately detect damage occurring closer to the installed location. Also, strain measurements do not provide any information related to the loadings impacting the module.

Considering the features and limitations of the above-discussed sensors, it can be seen that all these sensors provide essential information required for assessing the structural response during logistic operations. Also, the combination of these sensors can allow us to capture the module's motion effectively, while the local damage can also be directly analyzed. However, the dynamic loading and structural response-related information these multiple sensors capture requires an integrated analysis. So that a holistic logistic impact can be analyzed and a damage scenario can be evaluated.

2.7 Damage Assessment Methods

Overall, the relevant studies of SHM can be summarized in two main categories based on their methodological approaches: model-based monitoring and data-driven monitoring. These approaches are further discussed in the following sections and presented in Figure 2-6.

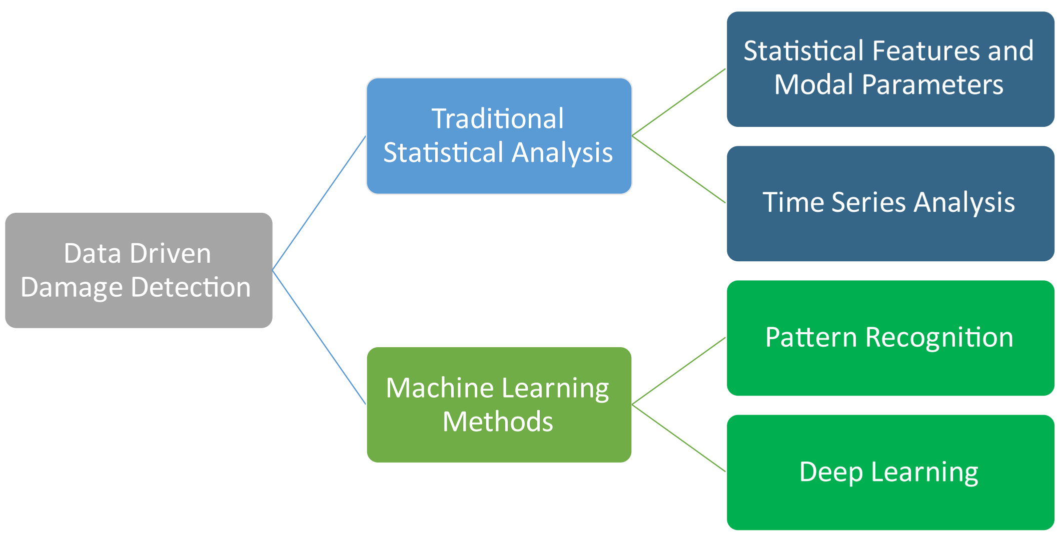


Figure 2-6. Common damage assessment approaches in SHM

2.7.1 Model-Based vs. Data-Driven Damage Detection Methods

Damage detection or Structural Health Monitoring (SHM) approaches can be broadly categorized into model-based and data-driven Approaches [110,215]. A model-based (physics-based) approach identifies damage by monitoring changes in the simulated measurements from a mathematical structure model. Such a mathematical model links a structure's input and output parameters using the structure's known or assumed physical and material properties. The finite element model (FEM) is the most popular model-based method due to its ability to handle complex geometries. When using the model-based approach, the FEM parameters are updated according to the applied conditions, or scenarios are simulated. The FEM model calculates an optimized solution of mass, stiffness, and damping matrices for new conditions and evaluates the consequent structural response. However, for efficient damage detection, these approaches have several limitations [369]: (a) model accuracy and reliability, (b) handling uncertainties, (c) flexibility to update the model under dynamic scenarios, and (d) requiring specialized knowledge about structural dynamics and conditions.

On the other hand, data-driven (signal-based) methods solely rely on statistical sensor data analysis to evaluate the structural response. These methods don't require the structure's material or physical properties, thus making them more desirable. The model-based methods have inherent uncertainties due to model assumptions and accuracy concerning real-world scenarios. Meanwhile, the time-series sensor data provides more accurate and realistic information about actual scenarios and reduces uncertainties [224]. Data-driven methods can adapt to new data without changing a predefined model. These methods can handle large amounts of data more efficiently than model-based methods. This is particularly important in SHM, where sensor data is often collected continuously over long periods [92]. In addition, data-driven methods can usually provide real-time monitoring, which is difficult with model-based methods.

2.7.2 Data-Driven Methods

With recent technological advancements, sensors can provide large amounts of time series data related to the loading impacts on structures and the consequent structural changes. Analyzing such data enables real-time and automated damage detection and structural health monitoring. The data-driven methods can be broadly categorized into two main categories: (a) traditional statistical paradigm and (b) Machine learning methods.

2.7.2.1 Traditional Statistical Analysis

Statistical Features and Modal Parameters

Generally, damage detection approaches assess the structural response under different loading environments and evaluate the variations. In this perspective, two types of structural responses can be static and dynamic. Assessing static responses such as stress and strain is straightforward but less reliable for evaluating structural changes [81]. Generally, the methods to determine static response focus on extracting the statistical features directly from the raw data. These features provide the signal's characterization and properties, such as mean, variance, skewness, and kurtosis of the signal, as well as the energy and entropy of the structure [182].

In the case of dynamic response assessment, the signal's modal parameters are more efficient [51,358]. The modal parameters, such as frequencies, mode shape, damping, etc., are more sensitive towards both rapid and steady structural variations. Therefore, they are more reliable than static features for detecting the structure's critical damage and lifecycle deterioration [97]. However, dynamic response assessment is difficult as it requires controlled operations and environmental effects to obtain the desired accuracy [110]. Also, the performance of such methods is inefficient for a real-world complex 3-D civil structure that poses nonlinear behavior under a dynamic loading environment, as these methods are only suitable for linear systems that exhibit proportionality between applied forces and structural responses [245].

Time Series Analysis

Time series analysis models the temporal behavior and provides insights into its dynamic behavior. These statistical tools simulate the dynamic characteristics using historical trends of the measured data. The most commonly used time series analysis models are the AutoRegressive (AR) and its moving average integrated variation called ARIMA, wavelet transform, and spectral analysis [143,250]. The AR model expresses the current value as a linear combination of past values. In contrast, ARIMA integrates the moving average into the AR to incorporate the weighted average of past error terms in the time series data [186]. Therefore, ARIMA is more suitable for handling non-stationary scenarios [250]. While ARIMA models are highly accurate under certain scenarios, they require manual parameter selection and tuning, making them computationally expensive [143]. Also, they rely on stationarity and invertibility assumptions and require excessive data preprocessing to deal with it [324].

Wavelet transforms, and spectral analysis tools such as Fast Fourier Transformation (FFT) and Power spectral density (PSD) are considered better than ARIMA, as these methods don't require conversion of stationarity [250]. These methods analyze the frequency and energy components and highlight the dominant frequencies in the signal. Therefore, they can distinguish between the amplitudes of different frequencies in the raw signal data. However, it is still challenging to differentiate between the frequencies related to the non-stationary loadings and those caused by the damaging condition [26]. Additionally, these methods have limited resolution to distinguish among minor variations, aliasing the frequencies at spectrum ends and sensitivity for noise-related issues [186].

2.7.2.2 Machine Learning methods

With the advancements in big data analytics and computing capabilities, machine learning methods are being adopted for SHM and damage detection [143,369]. The machine learning paradigm supports the development of regression models for large sensor data, which is impossible for traditional statistical tools. These machine learning methods are broadly categorized into statistical pattern recognition and deep learning models for damage detection.

Statistical Pattern Recognition

Pattern recognition methods compare the undamaged state with the new state under observation to assess any deviation. The pattern recognition approach, also known as unsupervised or novelty detection, is commonly used to identify the damage. These methods use the data's statistical distribution to determine the damage [290]. The simplest pattern recognition approach is to examine the control chart for any deviation in the pattern of the damage-sensitive feature [278]. More sophisticated methods include pattern recognition algorithms that use the statistical distribution of the data to identify the novelty [290].

Among conventional pattern recognition algorithms, k-means is one of the most commonly used algorithms for classifying vibration signal features [218]. It follows partition-based clustering to discover specified clusters in an unlabeled multi-dimensional dataset. It iteratively positions the centroid of clusters, starting from an initial set of centroids, where centroids represent the average of all the points in that cluster [11,268]. For k-mean, the optimal number of clusters is usually estimated using the silhouette or elbow methods [292,355]. This approach has been widely used for monitoring the performance of concrete bridges [79] and multi-story buildings [234]. Similar to the k-mean method, mean shift clustering is partition-based clustering. The main advantage of this method is it automatically estimates the optimal number of clusters based on the kernel density estimation (KDE) of input data. Also, this method does not impose any predefined shape on the data clusters.

Zhou, et al. [376] evaluated the performance of the agglomerative clustering method for damage classification of a concrete bridge. These studies reported better classification results than other methods regarding false-positive or false-negative. Despite its reported effectiveness, the agglomerative method cannot work with missing data and may produce arbitrary decisions. Some studies applied the density-based spatial clustering of applications with noise (DBSCAN) method for damage classification[93,129,181]. Heravi, et al. [129] evaluated the performance of modal strain energy as a damage feature using the DBSCAN method. [93] applied this method for damage detection and localization, and Li, et al. [181] used it to auto-identify the modal parameters. [315] developed an accelerometer-based system to collect data on prefabricated modules during transportation. Then, the acceleration-time series data was compared, and the performance of different statistical clustering methods was compared. He found that the DBSCAN classification was the most accurate [91,98]. Despite successfully demonstrating pattern recognition methods, they struggle with accuracy due to limited training data and scenarios [35,221]. These methods are less effective against a new class of damage incurred or are highly sensitive to noise. Also, these methods have limited capabilities to handle large-scale complex data and perform sensor fusion for multiple sensor data [308].

Deep Learning Methods

The deep learning paradigm has the potential to deal with complex data sequences, extract useful features, and model deep relations across multiple strings of sensor data. A deep learning approach helps incorporate a range of features from various sensor data streams and also extracts hidden features by exploring the correlation among the given set of features. Recently, several studies adopted deep learning methods for damage assessment and prediction [55,153,157,167,262]. Generally, using deep learning methods, a model is developed using data from the healthy, undamaged state of the structure. The trained model is then used to predict features for the new state according to input data. The accuracy of the predictions indicates the deviation of the structural condition from a healthy state [202]. Such an unsupervised approach is also known as the out-put-only model [107].

The most basic class of such deep learning models belongs to artificial neural networks (ANN) [262]. Due to its biological neurons-based solving algorithm, ANN has been identified as a powerful and reliable modeling approach for solving complex problems such as classification and pattern recognition [101,116]. Since the 1980s, different types of ANNs have been developed and applied effectively to SHM. Such algorithms include back-propagation NN [357,374], self-evolving NN [306], radial basis function NN [225], Bayesian NN [311], ANN predictive control algorithm [158], ensemble neural networks [95], general regression neural network [197], and auto-associative NN [119,139,189,374]. In addition to the raw sensor data, these methods also use modal parameters, such as modal frequencies, time-series coefficients, frequency response functions, etc., to detect damage.

a) Convolutional Neural Network

Despite the large application of ANN for damage detection, its performance is limited due to gradient descent issues, nonconvex errors, large data set requirements, and extensive computational resources for complex data structures [48]. A more advanced, convolutional neural network (CNN) performs better when dealing with such issues [219,303]. CNN architecture consists of convolutional, pooling, and fully connected layers. The convolutional layers apply filters (called kernels) to the input data streams and extract spatial hierarchies of features by analyzing the patterns and relationships across data streams. Pooling layers reduce the spatial dimensions of the input data, making it computationally more efficient and improving accuracy [309]. The connected layers (dense layers) combine high-level features and generate output layers [301]. Such powerful architecture showed promising results in several studies for damage detection [219,301,303,309,366].

Despite its successful application in many studies, CNN cannot incorporate the relations across several time intervals. CNN is inherently designed for learning in the spatial dimension only, i.e., capturing the relations among the features at each instance [18,302]. In the case of structural damage detection, the time series data also has temporal dependencies that need to be incorporated into the model for efficient performance [47]. From this perspective, a modified one-dimensional CNN architecture can learn the features of a single temporal dimension [309]. The filters in the one-dimensional CNN learn the features in a given sequence window instead of individual instances, making it more robust than the typical CNN architecture. One-dimensional CNN poses better generalization and reduces overfitting issues. However, this CNN variant can only explore the data dependencies within a short range of a sequence and does not learn the dependencies across different sequences in a time series. Therefore, it is still less effective for the time-series data where dependencies occurs not only within a short sequence but also among different sequences.

b) Recurrent Neural Networks

A recurrent neural network (RNN) method is considered an alternative to CNN, as it overcomes CNN's limitations. RNN is a type of neural network that learns across the temporal dimension of the data [260]. These models maintain hidden states across time steps, capture sequential patterns, and thus model the sensor data dependencies across the temporal sequences. In contrast to one-dimensional CNN, RNN methods are suitable for capturing long-range dependencies in a time series. RNN has a simple architecture with feedback connections that consider the activations from previous instances in the sequence to influence output. In other words, it has a mechanism to remember and use previous information for processing the next instance. This approach makes RNN better suited for time series data of structural damage detection. However, RNNs struggle with vanishing gradients problems, especially in long sequences. During training, RNN uses gradient descent to update weights for optimal solutions. However, the gradients become small during backpropagating errors, causing poor weight updating. This issue causes poor capturing of long-term dependencies in the data and slow model convergence.

Long short-term memory (LSTM) and gated recurrent units (GRU) are more advanced models in the RNN paradigm that resolve the issues faced by RNNs. These models have more complex architecture, enabling them to handle longer sequences by maintaining memory over time. The architectures are presented in Figure 2-7. The LSTM architecture consists of additional input, output, forget gates, and memory cells [275]. The input gate (i_t) controls the new information flow to the memory cell (C_t), activated by the current input (x_t) and the previous hidden state (h_{t-1}). Forget gate (f_t) controls the irrelevant information to be discarded from the memory cell. Meanwhile, the output gate (o_t) determines the data to be passed to the LSTM output. Typically, the $tanh$ (-1,1) and σ (0,1) functions are used to control the information flow across the input, output, and forget gates and memory cells.

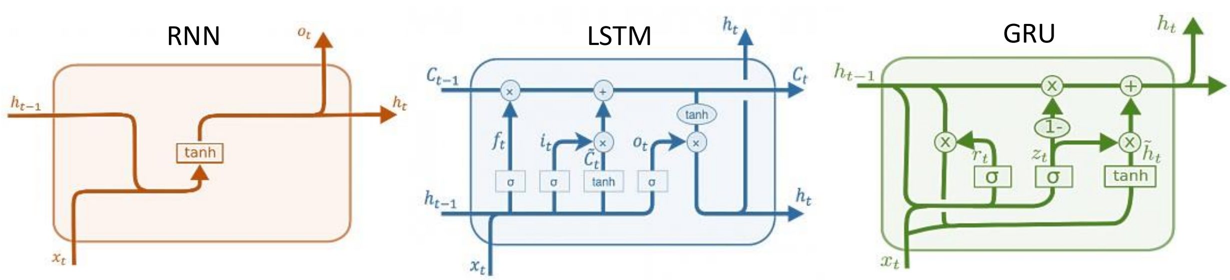


Figure 2-7. Comparison of RNN, LSTM, and GRU architectures

A dedicated memory cell in LSTM improves its efficiency in handling long-term memory; however, it makes it computationally more expensive. In contrast, GRU has a simplified architecture containing only a reset (r_t) and update (z_t) gate. It combines the roles of input and memory gates in the reset (r_t) gate, which decides how much the previous hidden state is to forget and new input is to be included [254]. Meanwhile, the update (z_t) The gate decides to retain the part of the previous state information and pass it on to output. Such an approach reduces the need for a memory call and makes it computationally more efficient than LSTM while maintaining accuracy.

Although the RNN class models perform better for the timer series data, these models still lack the efficiency to learn the features across multiple series of features. For example, these models will capture dependencies across time dimensions only for data containing several feature time series. However, it lacks the ability to capture the correlation across spatial dimensions, i.e., correlation among variables or features [254]. To deal with this issue, researchers have applied combinations of CNN and RNN class models to detect structural damage accurately. The combined CNN-LSTM model was used for damage detection in the structural components while utilizing this combination's spatial feature extraction and long-term sequential memory capabilities [72,366]. In this approach, CNN captures the relations among the features at the local level, whereas LSTM captures the dependencies in global sequences.

Some studies preferred GRU over LSTM due to its faster and more efficient architecture. With fewer parameters, GRU is less affected by the overfitting issue while effectively training across sequences. Some studies effectively combined CNN and GRU for structural health assessment [170,346]. In such hierarchical architecture, the first spatial features are extracted using CNN and are passed to GRU for further reinforcement learning across the temporal sequences. However, in some cases, the hierarchical combination of CNN and GRU experienced gradient disappearance issues [47]. A more advanced variant, a bi-directional gated recurrent unit (BiGRU) model, is used to deal with such issues [345]. A BiGRU model includes two GRU cells working together in opposite directions (forward and backward) to improve learning across the temporal dimension.

Palaell vs. Hierarchical Architecture of Combined Deep Learning Models

For combining the effect of two deep learning models, they can be either linked in parallel or in a hierarchy. In this context, the choice of architecture mainly depends on the data characteristics and objective to focus on either spatial or temporal dimensions. For parallel combination, the input data is provided to CNN and GRU simultaneously, and both models work exclusively to generate output. Each sub-model extracts different features, such as CNN extracting spatial features and GRU capturing information in temporal sequences. Then, the output from both models is merged by multiplication and average pooling to generate a combined output [345]. Several studies have applied parallel architecture to incorporate the effect of different deep learning models [47,345,367,378]. Although parallel architectures equally focus on both dimensions, they are more complex, computationally expensive, and less efficient for large data sets [266].

Considering this, some other studies adopted hierarchical architecture [346,371]. In hierarchical combination, CNN is first applied to the input data to extract spatial features from raw data. Then, CNN output is passed to the GRU model to capture the information further along the temporal sequences. This approach allows CNN to focus on local spatial patterns at each time instance, whereas the GRU focuses on capturing the variation across the temporal sequences. Such an approach is more desirable when the input data contains a dynamic hierarchy and the objective is to explore across hierarchies in all dimensions [38,49].

2.8 Knowledge Gap

The critical findings and knowledge gaps identified from the reviewed literature are summarised below.

a) The research focuses very little on the logistic operations of modular construction projects. Notably, the impact of logistics operations on the module's structural performance has not been investigated.

b) FEM-based structural performance assessment is impractical as the simulated loading scenarios cannot represent accurate and actual logistics operations. Also, these approaches cannot monitor structural performance in real-time. On the other hand, data-driven methods acquire large data points for the damaged state of the module.

c) When selecting any damage assessment model, defining the damage level intended to be assessed correctly is important. In a freshly manufactured structure, some damage at the material level always exists, which is commonly called a defect. Such defects can grow into larger structural-level damage under exposure to new loadings. This structural-level damage can further increase to the extent that the structure loses its intended function, which is called failure. Typically, the damage detection approach should be able to detect the damage which may lead to failure.

d) The time between damage initiation and detectable damage development is very significant. Therefore, the sensing platform should be capable of recording all the critical data.

e) Data-driven damage assessment methods must mostly compare structure states to evaluate change. The unsupervised algorithms can assess the damage occurrence and its location. However, exact damage quantification can only be obtained by using supervised algorithms.

f) Supervised algorithms need damaged state data for training, which is normally unavailable for MiC logistics operations. Unsupervised approaches can be trained using undamaged state data only.

g) Raw sensor data do not help to assess the damage. Therefore, extracting the damage-sensitive feature and transforming the raw data of sensors into damage-related information is essential. A sensitive damage feature is also sensitive to changing environmental conditions. So, the damage-sensitive feature should be intelligently selected.

h) The algorithm that is sensitive to damage is also sensitive to noise. Therefore, the noise reduction phase of an algorithm is vital; for example, if there is a high range of frequency excitation, the detectable damage size will be reduced, and the complexities of the structure will increase with increasing damage.

i) The deep learning convolutional models only learn features in one direction, i.e., among the different sensors at individual timesteps. However, the sensor data for dama assessment have significant correlations among the sequences in the time domain.

j) The Sequential deep learning models capture correlations across the time dimensions.

Chapter 3

RESEARCH METHODOLOGY

This chapter elaborates on the methodology of the proposed objectives. Each objective has its discrete methodological steps to achieve the goals. The methods of each objective are explained in detail in the subsequent section.

3.1 Methodology for Analyzing the Influencing Factors of MiC Logistic Operations

(Objective I)

The overall methodology of the first objective is illustrated in Figure 3-1. The first part of this methodology, "the article search and screening," is discussed in section 2.2.1. Further methods for analyzing the factors are presented in the following sections.

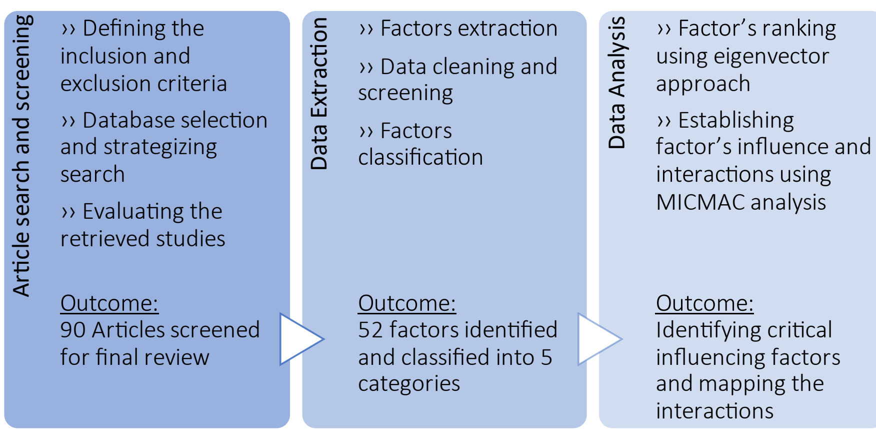


Figure 3-1. Overview of methodology for exploring influencing factors of MiC logistics SC

3.1.1 Extracting the factors related data

The selected studies were thoroughly reviewed, and qualitative data were extracted. To highlight the comprehensiveness of selected articles, the focus of reviewed studies (such as sustainability, SC collaboration, and risk, etc.) and the nature of factors in those studies (such as success factors, barriers, risk factors, influencing factors, etc.) was evaluated. For this purpose, the authors assessed the scope and connotation of the studies after reading each research article. Afterward, an inductive qualitative coding process was adopted for factor extraction. The inductive qualitative coding process is a bottom-up iterative approach in which raw data is extracted, analyzed, and coded to develop a consistent narrative [305]. Following this approach, all the factors mentioned in each study were listed in a structured Excel sheet. Then, after analyzing the description and connotation, the factors in each study were coded. The systematic and iterative coding process established a concise and consistent list of factors. Finally, the coding in each study was used to calculate the factor's frequency of occurrence.

3.1.2 Analyzing the Factors of MiC Logistic Operations

A quantitative interpretive research approach is adopted to examine the influencing factors of MiC SC. This approach explores a system in reality through subjective intervention and interpretation [136]. In the quantitative interpretive approach, the statistical data and modeling tools are integrated to discover the underlying knowledge by exploring the causality of data. Such an approach can yield more meaningful and comprehensible results for establishing a knowledge base and developing policy [33].

This study uses the factors' co-occurrences in the literature for analysis. The co-occurrence of factors defines their significance and potential associations with each other [57]. It is assumed that factors are closely related to each other if they appear together in a greater number of studies [377]. Such co-occurrence-based associations draw a semantic network, which helps analyze the relationships between different elements, concepts, or ideas [102]. Co-occurrence networks are commonly used in various research disciplines.

The bibliometric & scientometrics reviews [57] and information sciences [177] related studies have used this approach to study the themes of knowledge and draw critical trends. Similarly, in social sciences [135] and health sciences [150], studies performed factor analysis and explored the association of different elements. This paper utilized a co-occurrence network of factors to investigate their association levels and further categorized them to identify the critical factors. First, the significance of factors is estimated using eigenvector weight calculations. Then, the MICMAC (the cross-impact matrix multiplication applied to classification) analysis tool is used to develop a co-occurrence network. The detailed methodology of eigenvector and MICMAC is explained in sections 2.4.2 and 2.4.3.

3.1.2.1 Ranking of factors using Eigenvector weight

In systematic reviews, frequency of occurrence is the most common metric for ranking the factors [114,277,337]. However, only using occurrence data can yield misleading results, particularly for an extensive list of factors, where a factor's occurrence is inconsistent across the scale. Moreover, the factors' transitivity may also affect the true significance of the factors [252]. Adopting a relative occurrence approach with a principal eigenvector in such a scenario can provide the best ranking on a ratio scale [106,251]. Faqih, et al. [96] also adopted a similar approach for calculating the factor's ranking.

For estimating the eigenvector weighting, a cross-sectional matrix (A) is developed. Each value in the rows (i) of the matrix (A) represents the relative difference of occurrences corresponding to other factors in each column (j). The relative difference in frequency (a_{ij})

is the frequency in a row (a_i) divided by frequency in column (a_j) [96]. Consequently, the matrix A is a $n \times n$ matrix of a_{ij}, where $A \in \mathrm{R}^{n \times n}$ (Equation 3-1). Also, matrix A fulfills the conditions in equations 3-2 to 3-4, as required by the eigenvector method [251].

$$A = \begin{bmatrix} 1 & a_{12} & a_{13} & \dots & a_{1n} \\ 1/a_{12} & 1 & a_{23} & \dots & a_{2n} \\ 1/a_{13} & 1/a_{23} & 1 & \dots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1/a_{n1} & 1/a_{n2} & 1/a_{n3} & \dots & 1 \end{bmatrix} \qquad \text{Equation 3-1}$$

$$a_{ii} = 1 \qquad \text{Equation 3-2}$$

$$a_{ij} > 0 \qquad \text{Equation 3-3}$$

$$a_{ij} = \frac{1}{a_{ji}} \qquad \text{Equation 3-4}$$

$$w_i = \frac{1}{n}\sum_{j=1}^{n} \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \quad where \quad i, j = 1,2,\dots,n \qquad \text{Equation 3-5}$$

Further, for calculating the factor weights (w_i) first, the column vectors of the matrix (A) are normalized, and corresponding rows are added. Then, the matrix is further normalized to get the eigenvector weights w_i (Equation 3-5).

3.1.2.2 Factors classification using MICMAC Analysis

MICMAC efficiently classifies the factors based on their influencing relationships [259]. In this method, first, a factor's co-occurrence matrix is developed. Then, the relative co-occurrences of factors are calculated using the z-score normalization approach [239] (Equation 3-6). Each value in the normalized influence matrix (wc_{ij}) explains the degree of influence, such as, 0 not influencing, 1 slightly influencing, 2 moderately influencing, and 3 highly influencing.

$$normalized\ wc_{ij} = \frac{wc_{ij} - \min wc_i}{\max wc_i - \min wc_i} \times 3 \qquad \text{Equation 3-6}$$

$$influencing\ \ Power = \sum_{j=1}^{n} wc_{ij} \qquad \text{Equation 3-7}$$

$$dependence\ Power = \sum_{i=1}^{n} wc_{ij} \qquad \text{Equation 3-8}$$

The relative co-occurrences of factors indicate the co-occurrences among two factors with respect to the total occurrences of a factor. This way, the influence power indicates the capacity of a factor to impact other factors. In contrast, the dependence power indicates the tendency of a factor to be affected by other factors. The direct influence and dependence powers are determined using Equations 3-7 and 3-8, respectively. Then, the indirect influencing and dependence powers are calculated after iteratively increasing the power of the matrix till the stable matrix is achieved. The indirect influence matrix reduces the number of factors in the system by removing the factors having indirect influences. Finally, the direct and indirect analysis results are plotted on influence maps, classifying them into four categories based on their influence and dependence powers. For further interpretation, MICMAC results are compared with eigenvector weights and co-occurrence ratios (CoR) of factors. Such a combined analysis approach provides additional depth for a better interpretation of results [4,241]. Also, the influencing relationships among factors in each category are analyzed. The categories are interpreted into four themes, which explain the influencing system of factors.

3.2 Methodology for Exploring Technologies for MiC Logistics Supply Chain

(Objective II)

The overall review methodology has three phases (see Figure 3-2). A detailed systematic approach was adopted in the first phase to select and screen the relevant articles. Text analytics were then used to extract the relevant data from the selected articles. Finally, the data was analysed and synthesised in the third phase to determine the synergies among MiC challenges and potential technologies. Further details are discussed in the following sections.

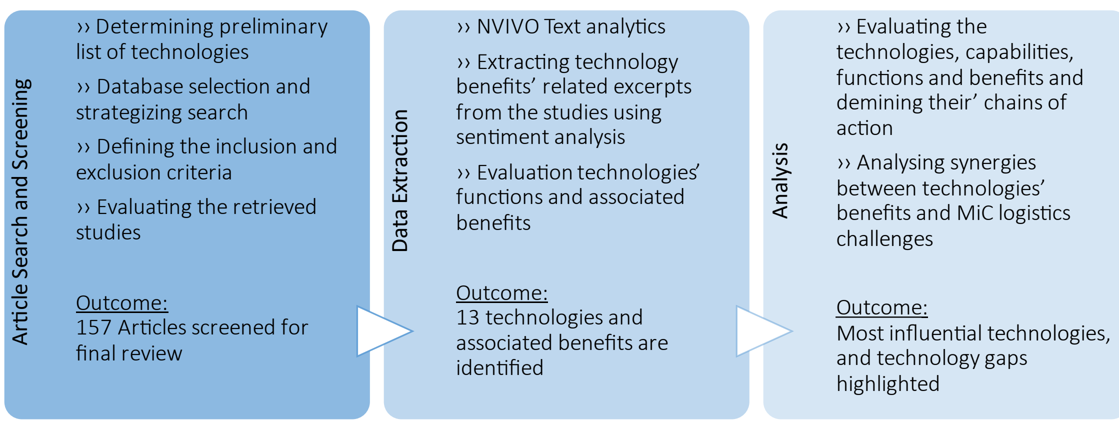


Figure 3-2. Overview of methodology for exploring technologies for MiC logistics SC

3.2.1 Article search and screening

The review aims to investigate the application of contemporary technologies in the logistics and supply chain area. In the first step, we determined a preliminary list of technologies for the supply chain. The keywords 'technology' and 'supply chain' were used to search a thorough list of articles (1457). The author-provided keywords in these articles were listed, and an exhaustive list of 19 technologies was identified among these keywords. Based on the identified technologies, an explicit search query was generated to search all the articles related to the application of technologies in logistics and supply chain published since 2010. The identified list of technologies was included in the keyword list of the search query.

The query was performed on Scopus and Web of Science (WOS) databases. These two databases are considered adequate and sufficient for searching research articles because of their broader coverage, rapid indexing process, and access to recent publications compared to other databases [207]. The exclusion criteria for the search are defined to focus only on the articles related to different technologies in logistics and supply chains. The search was limited to engineering journal articles about applying technologies in logistics and supply chains. Articles related to medicine, social science, aerospace, automobile, etc., were excluded using the database filters. As a result, a total of 2,001 articles were identified. The article screening process follows the PRISMA flow (see Figure 3-3).

Articles were further evaluated based on their focus and scope relevancy by reading titles and abstracts. Resultantly, only 285 articles were found relevant (removing n=1716). These selected articles were thoroughly read and assessed against the two inclusion criteria: (1) the article covers the application of technology for logistics or supply chain operations, and (2) it highlights the benefits obtained through technology application. As a result of the inclusion criteria screening, 151 articles are shortlisted. Subsequently, forward and backward snowballing was also conducted to exhaust the possibility of overlooking relevant publications on the subject matter. As a result, 157 articles were finally selected for further review and analysis.

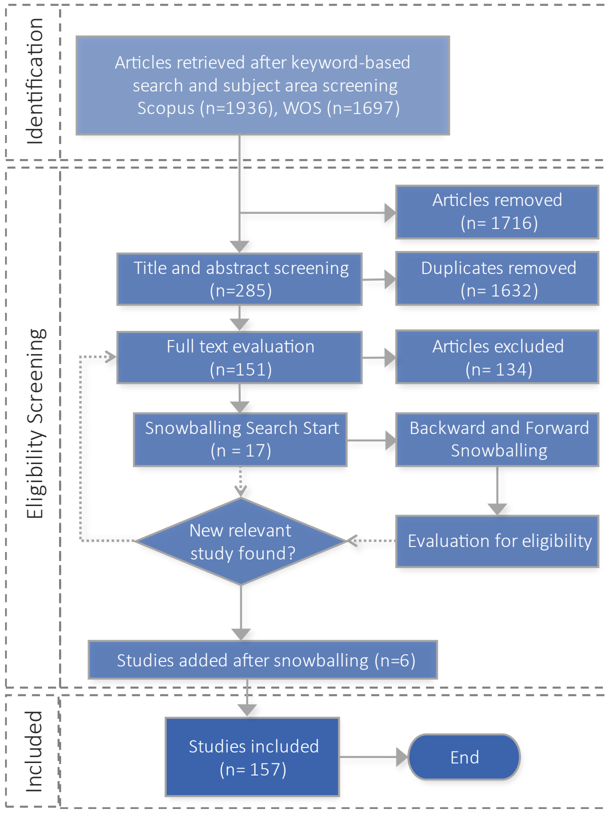


Figure 3-3. PRISMA flow chart for article selection and screening

3.2.2 NVIVO text analytics-based data extraction

The text analytics approach helps to systematically extract valuable information and insights from large amounts of unstructured text data. An effective qualitative data analysis tool in this regard is NVIVO, known for its ability to manage and analyse qualitative data and conduct literature reviews [36]. NVIVO ensures consistency and transparency of analysis, allowing tracking of records and helping interpret the results. This tool was therefore employed to perform text mining of the screened studies, and it helped identify, organise, and analyse the benefits and attributes of supply chain technologies.

In this study, text mining is performed only to identify relevant excerpts (or statements) from literature where technologies' benefits, advantages, and positive outcomes were mentioned. For this purpose, a dictionary-based sentiment analysis approach in NVIVO was employed. This approach adopts pre-defined words or phrases to identify the extracts with positive or negative sentiments. All the excerpts having positive connotations were identified (5765). Among these excerpts, many contained insignificant, trivial information. The authors manually evaluated these excerpts and shortlisted only those containing significant information about technologies' benefits, advantages or positive applications. Around 750 such extracts were shortlisted and coded for further analysis and evaluation.

3.2.3 Technologies' chains of actions and Synergy analysis

A qualitative synergy analysis evaluates the potential interactions or nexus between different elements in a system or process [108]. Such analysis has been used in business and scientific research to integrate various systems' components for enhancing performance, efficiency, and effectiveness [41,64,296,318]. In this study, we adopted the synergy analysis technique to systematically evaluate the suitability of different technologies to address various MiC challenges. In the first step, the excerpts identified from the text analytics in NVIVO were further analysed to determine the chains of action of any benefit (see Figure 3-4). A "chain of action" explains how any technology supports achieving any specific benefit at the local or global level in any supply chain. These chains of actions highlight features, capabilities, and processes contributing to a particular technology benefit.

The purpose of identifying the chain of actions is to understand the mechanism of technologies that impact the system and deliver any particular benefit. For instance, as shown in Figure 3-4, one excerpt related to Blockchain advocated that its 'function' is to improve delivery reliability, which helps improve profit. Initially, 110 chains of actions were established by evaluating all the excerpts related to all the technologies (given in Appendix–C). Similar chains of actions with common synergies with the challenges were grouped to provide 57 benefits from different technologies.

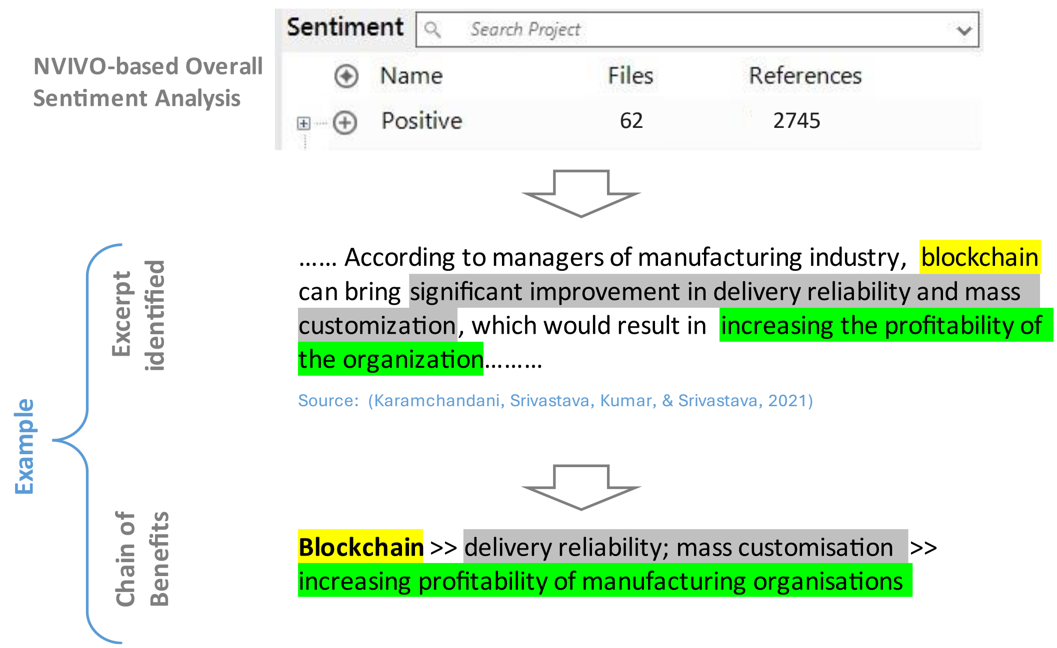


Figure 3-4. Process of extracting technology-related benefits from sentiment analysis

These chains of actions were further used to assess the synergies between any technology and MiC challenge. This approach of associating a technology's chain of action with a challenge is more systematic and assertive. It helps to relate a challenge with a technology's functional attribute instead of any subjective benefit-related statement. A detailed table of synergies is developed, indicating all the substantial synergies between technology benefits and challenges, as shown in Appendix – D. These synergies highlight the relevance and importance of any technology for MiC logistic operations. The review study has also discussed the current state of technologies suitable for MiC challenges, technology gaps, and future ways forward.

3.3 Methodology for Developing IoT-based Sensing Tool (Objective III)

The IoT Sensing devices' development process consists of five phases, as elaborated in Figure 3-5. The existing sensing technologies are reviewed in the first phase, and suitable sensors are selected. Then, different manufacturers' alternatives were compared for the selected sensors to choose the high-performance, low-power consumption alternative.

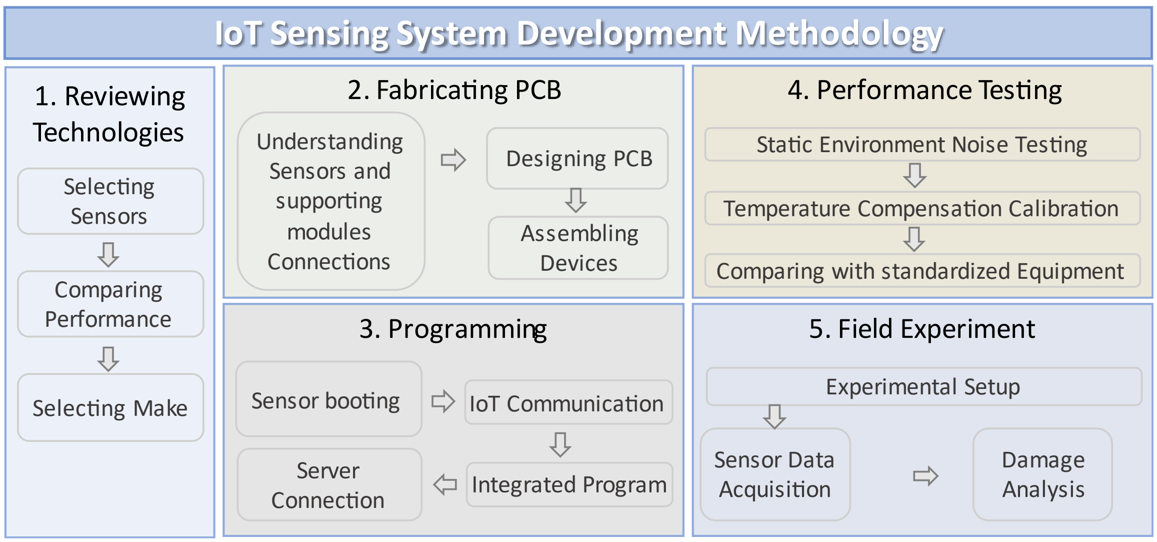


Figure 3-5. IoT Sensing System Development Methodology

In the third phase, the selected sensors' functions and connections were understood for the integration. After that, the PCB was designed to integrate all the sensors, their essential supporting components, and IoT communication modules. Following that, the sensing devices were assembled. The developed sensing devices were thoroughly tested for noise evaluation in the next phase. Then, a temperature compensation model was developed to calibrate the strain measurements. Finally, in the last phase, a detailed field experiment was demonstrated to the application of the developed system for MiC logistic operations.

3.3.1 Sensor Selection

To monitor the MiC module's damage, safety, and structural health, it is essential to measure its structural response continuously. However, the MiC module generates a non-stationary structural response during highly dynamic logistic operations. Monitoring such non-stationary structures is highly challenging, where both the structure and the impacting loads are moving [80]. The most existing technologies and methods for damage and structural health monitoring (SHM) are designed for traditional stationary structures [328]. The structure of a traditionally constructed building is mostly monolithic, where structural response at any location on the building can be sensed or estimated from any other location apart. However, in the case of MiC, the building comprises separate building blocks (modules), where damage in one module cannot be detected from any other module, as they are not joined monolithically. Therefore, several sensors must be installed on each module individually to monitor each module's structural response and performance.

The most commonly used sensing technologies for SHM are (a) Vibration-based, (b) strain-based, (c) guided waves, and (d) acoustic emissions [120]. Table 3-1 summarizes the sensors and features of each sensing technology. The acoustic emission and guided wave technologies follow an active signal response estimation principle [53]. A short pulse/signal is induced in the structure, and the sensors installed at different locations sense the response. The variation in the sensor's measured response leads to an estimate of the variation in the structural condition. These techniques are considered suitable for mid-range assessment and acquiring sophisticated equipment and a static environment for signal induction. Thus, using these technologies for MiC module structure monitoring during highly dynamic and non-stationary logistic operations is unsuitable.

Table 3-1. Commonly used sensing technologies for structural response monitoring.

Technology	Sensors	Features
Vibration-based	Accelerometers	Global range, limited resolution, sensitive to environmental conditions and disturbances
Strain-based	Foil Strain Gauge, Piezoelectric Sensors, FBG Sensors	Local range, limited resolution, high sensitivity, sensitivity to environmental conditions, accurate damage quantification,
Guided waves	Piezoelectric Sensors	Mid-range, high sensitivity, not suitable for thick composite materials, sensitive to noise
Acoustic emission	PZT acoustic wave sensors, AE probes	Mid-range, not suitable for thick composite materials, sensitive to noise

On the other hand, the strain gauge and the vibration sensors don't require any standard signal induction, and they measure variation in the structural response under different environmental and loading conditions. The strain gauge sensors can directly estimate the structural deformation or displacement locally. Meanwhile, the variations in the vibration response can help assess global structural changes. Also, the linear vibrations and rotational speed variations effectively capture the structural movement, which can help estimate the impact of loadings induced by the motion. A multi-metric sensor containing an accelerometer and gyroscope would be beneficial for monitoring such motion. Since the module lifting, loading-unloading, and assembly operations involve the tilt and rotation movement of the module, its impact on the structure and corresponding response must be monitored [287].

Considering sensors' sensitivity, range, and portability, the accelerometer for vibration, gyroscope for rotational speed measurement, and strain gauges are most suitable for monitoring MiC modules during logistic operations. However, the commercially available accelerometer and strain sensors are not integrated and have separate control, support, and communication systems, such as computers, wireless gateways, and battery or power supply. Each MiC module requires a dense array of sensors to monitor logistic operations effectively. Installing several large commercially available sensing systems on a single MiC module is impractical.

3.3.2 Selected Sensors' Damage Monitoring Approache and Scope

Three sensors, strain, accelerometer, and gyroscope, are selected to monitor the module's structure. A strain sensor is capable of measuring the direct variations in the structure. However, further analyses are required to understand and estimate whether the variation is substantial, highlighting the damage or whether such variation is within the material plasticity range. On the other hand, the accelerometer and gyroscope primarily measure the force impacting the structure as linear and rotational accelerations. Meanwhile, such 3-directional accelerations can also indicate the structural variations indirectly. Such an approach has been widely adopted for structural health monitoring and leak detection through signal analysis [117,141].

This signal analysis approach evaluates the signal's excitation (vibration) patterns under a specific force (loading conditions). A particular impacting force will have a specific vibration pattern corresponding to the structural properties. Under the same impact, the vibration response will differ if any structural variation occurs. Comparison of such variations across multiple sensors installed at various locations can help assess the level of damage.

3.3.2.1 Relative sensor data vs Materials' threshold-based approach

In this context, comparing a strain variation with the material plasticity threshold can also play a significant role in identifying the damage. However, such a comparison is only possible if the sensor is installed exactly over the damaged location. In such a case, installing enough sensors to cover the whole module structure is impractical. Therefore, we adopt a relative sensor data assessment approach. For example, suppose eight sensors are installed at the corners of a module, and one indicates different variations than the other seven under the same impact conditions. In that case, such a sensor must indicate an abnormality near its installed location. As illustrated in Figure 3-6, sensor S6 shows a different response than all other sensors, suggesting a potential structural abnormality closer to this location.

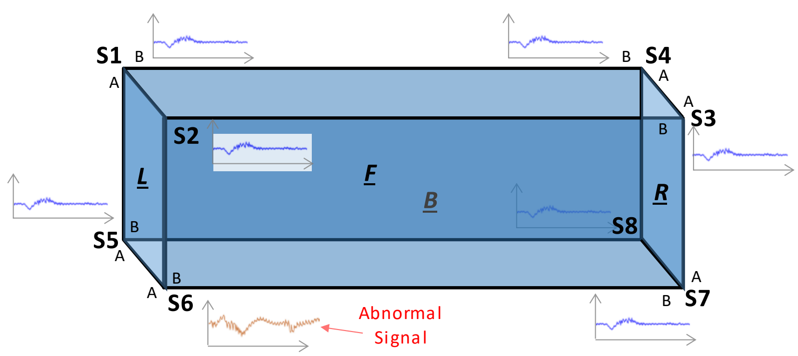


Figure 3-6. Example illustration of relative sensor response-based damage monitoring

Following such an approach, the statistical comparison of sensor data can provide further details about the level of abnormality and its relative location. Statistical and signal analysis methods can sufficiently help evaluate the factors' response, such as moving windows and strain field histograms.

Following are some other advantages of the relative sensor data approach over plasticity threshold: (a) it can monitor the whole structure with fewer sensors, (b) it offers effective assessment under varying loading conditions during logistic operations, (c) it offers more generalisability for all kinds of material structures, (d) material plasticity thresholds lack accuracy, even materials with the same compositions and properties may possess different plasticity ranges, (e) the relative sensor data approach can also be used for other indirect structural response measuring sensors (accelerometer and gyroscope), and (f) a consistent approach for multiple sensors can enable sensor fusion approach to measure the structural response more effectively.

3.3.2.2 IoT sensing system damage sensitivity and scope

Microscopic defects can always exist inside the materials of a manufactured or constructed structure. These minor defects often go undetected by commonly used instruments. Such defects typically do not cause concern as they remain within the materials' plasticity range. However, these defects start causing internal deterioration in certain conditions, and a crack initiation phase begins, as shown in Figure 3-7. In the crack propagation phase, such internal deterioration grows beyond the plasticity range, and cracks become visible. Finally, such cracks can further lead to structural-level damage or failure.

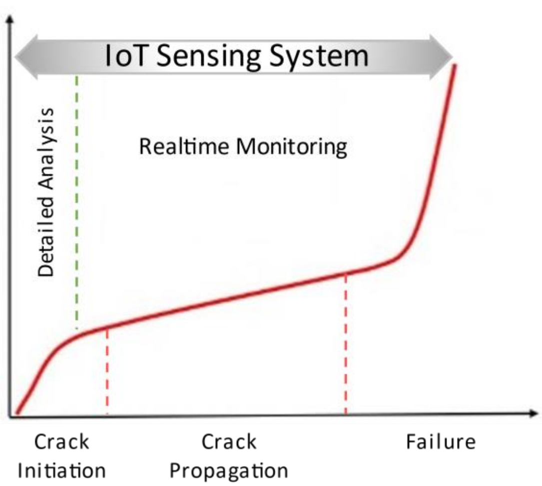


Figure 3-7. IoT sensing system damage assessment sensitivity.

Typically, a damage detection approach should be able to detect the damage as early as possible. The developed sensing system is sensitive enough to assess the damage at the crack initiation phase. However, such an assessment will require an in-depth, detailed analysis of the sensors' data to confirm any defect at a minor level. If the damage is within the crack propagation phase or beyond, the raw sensor data from the sensing system can show such structural variations in real.

Considering the capabilities and sensitivities of the developed multi-sensing system, it is competent enough for lifecycle structural health monitoring of MiC modules. Once installed on the module during manufacturing, it can monitor all the module handling within the factory. Therefore, it can also be used to inspect the structural performance of freshly manufactured modules. During the transition, it can monitor the structural response as well as the level of any impact on the module. During storage, it can monitor the impacting strains on the structure and warn about any uneven and unsafe stacking situation. It offers real-time module safety during assembly and other loading and unloading operations. Most importantly, the sensing system will remain installed on the module and continue structural monitoring during the building use phase.

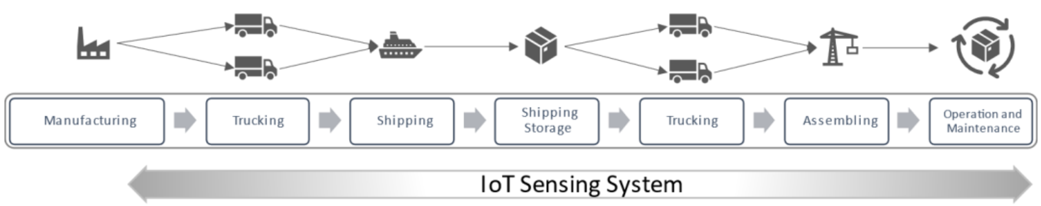


Figure 3-8. IoT sensing system lifecycle damage monitoring.

3.3.3 Sensing Device Design Rationale

Recent advancements in the Internet of Things (IoT), sensing technologies, and microcontrollers enabled the development of integrated sensing systems. Following this, Spencer, et al. [285] developed modular-type sensor boards (nodes) for acceleration and strain measurement. Each node has a different sensor or module connected to each other to make a fully functional sensing system. Fu, et al. [104], Won, et al. [327], and Sarwar, et al. [258] expanded this system and demonstrated different application scenarios for bridges and precast structures monitoring. These application scenarios highlighted that the system has lesser portability, larger size, and higher power consumption. It has no sensors to measure rotational speed or tilt, which is essential for monitoring the MiC logistic operations [287]. Besides, it requires a PC-based base station closer to the monitoring site for real-time data acquisition. More recently, Khayam, et al. [166] developed a similar sensing system for monitoring the lifting of prefabricated girders. This system adopts more advanced MCUs and analog-to-digital converters (ADCs) to enhance strain measurement efficiency. However, the installed accelerometer range (±2g) is not enough to measure the impact of transportation scenarios. Also, the system lacks real-time data transmission and relies only on built-in SD card storage.

The MiC module requires installing several sensing units on each module to monitor the module structure effectively. Thus, the form factor of the sensing units is critical. Visibly large sensing units installed on the module may attract the building occupants' attention and cause interruption. However, the size of the previously developed sensing systems was significantly higher and less desirable for MiC Modules. Also, MiC logistics monitoring requires long-range communication to ensure the real-time monitoring of modules during transportation from remote areas.

3.3.4 IoT Sensing System Architecture

Considering the above-discussed requirement for MiC logistics and the limitations of existing sensing systems, the sensing devices are designed. The overall architecture of the proposed IoT-based sensing platform is presented in figure 3-9. As mentioned in the literature review, the IoT system has two parts: sensing and communication. The sensing part includes (a) an Accelerometer – MPU6050, (b) a Strain gauge – HX711, and (c) a Temperature & humidity sensor – DHT22. The accelerometer and strain gauge sense the structural response, whereas the temperature and humidity sensor allows the calibration of other sensors against the change in environmental conditions. The strain gauge has analog input and needs an additional amplifier (HX711) to transform its signal.

The communication part of the IoT platform includes (a) a Microcontroller, (b) a LTE transmission module – SIM7600CE-T, and (c) a Data logger – DFR0229. The communication part enables the storage and real-time transmission of sensor data. The proposed components of the IoT system are carefully selected among several commercially available variants to ensure the system's sophistication, capabilities, battery life, and platform size. The approximate size and weight of the proposed IoT sensing platform should be less than 3x2x1 inches and 150 gms after packing in the casing.

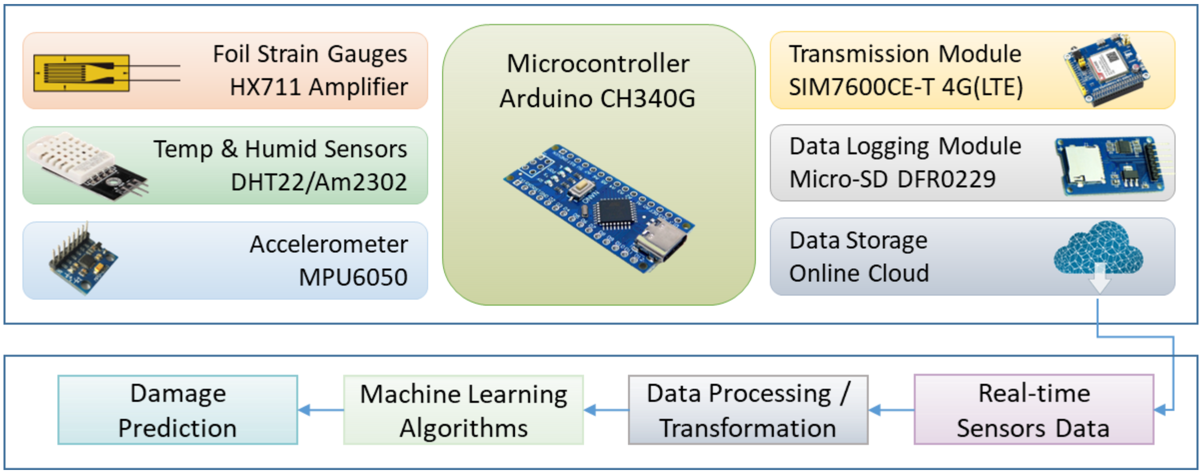


Figure 3-9. The overall architecture of the IoT-based sensing platform

3.3.5 IoT Sensing System Performance Testing

Different tests and calibrations are conducted to ensure the developed sensing system's performance and accuracy, as shown in Figure 3-10. IoT Sensing System Performance Testing. First, tests in a vibration-free static environment are conducted to assess the noise in the accelerometer and gyroscope. Followed by the required calibrations to improve the performance and accuracy. The strain sensor is tested under varying temperature conditions in the second phase. The strain drift under varying temperatures is resolved by developing the regression models to calibrate the sensor. Finally, the sensor performance is compared with a commercially available standardized universal testing machine (UTM).

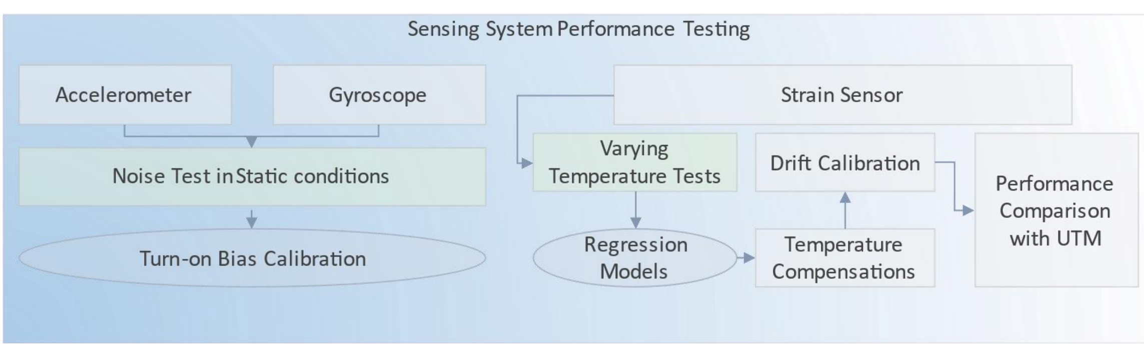


Figure 3-10. IoT Sensing System Performance Testing

3.3.6 IoT Sensing System Demonstration for MiC Logistics Damage Monitoring

This study presents various analyses to demonstrate how the sensor-measured response can be used to identify and estimate the damage in the module. These analyses analyze the real-time response of different sensors and evaluate the variations to detect any structural variation, deformation, or damage. The damage assessment strategy has two phases, as shown in Figure 3-11. In Phase 1, the damage and safety assessment analyses utilizing the real-time sensors' responses are presented. Different individual analyses are performed for each sensor type to identify the structural variations sensed by it. First, moving average and expanding average windows analysis are performed for strain sensors to determine the damage from the real-time sensors' response. Then, the strain field histograms and the Fast Fourier Transformation (FFT) spectrum magnitudes for the accelerometer and gyro are calculated. Finally, the results of all individual analyses will be compared and fused to confirm and validate the identified damage and assess its location.

Other than critical damage or cracks in the module, there could be undetectable deterioration in the overall module structure caused by the impacts of logistic operations. Such deterioration may reduce the module's useful life and require early unanticipated maintenance. In the second phase, the sensor fusion approach is adopted to estimate the overall impact on the module's health. Sensor fusion involves aggregating the relative impact sensed by each installed sensor. The impact is calculated based on the anomalies in the sensor's response. First, the anomaly detection approach identifies all the significant anomalies in the sensors' measured response. Then, these anomalies are systematically aggregated for different sensors to calculate the overall impact on module walls. Further details of the damage assessment processes are discussed along with the results in the following section.

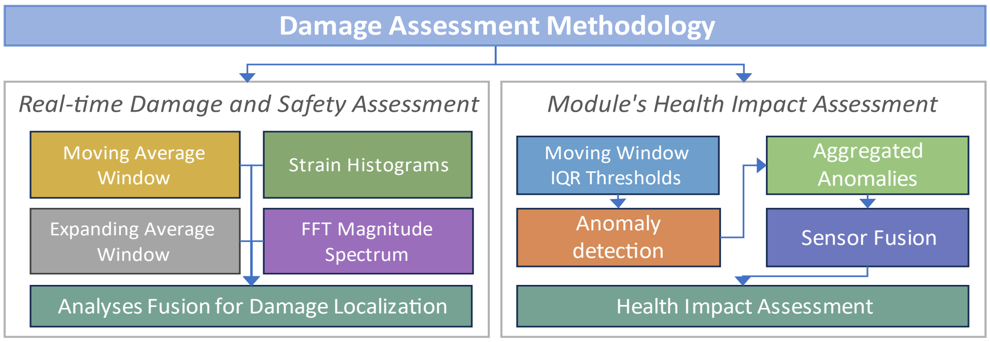


Figure 3-11. Damage Assessment Methodology

3.4 Methodology for Developing Hybrid Deep Learning Damage Assessment Model

(Objective IV)

The overall methodological framework is presented in Figure 3-12. In the first step, sensor data is obtained. Several sets of sensors should be installed on a module to fully sense the structural response of all the module elements, such as walls and joints. A set of sensors at each location includes an accelerometer, gyroscopes, and strain gauge, sensing seven time-series signals at each location. The acquired data is split into test and train portions in the second step, and the data shape is transformed into required sequences for training. The model architecture dictates the input shape and is crucial for the model to process data effectively.

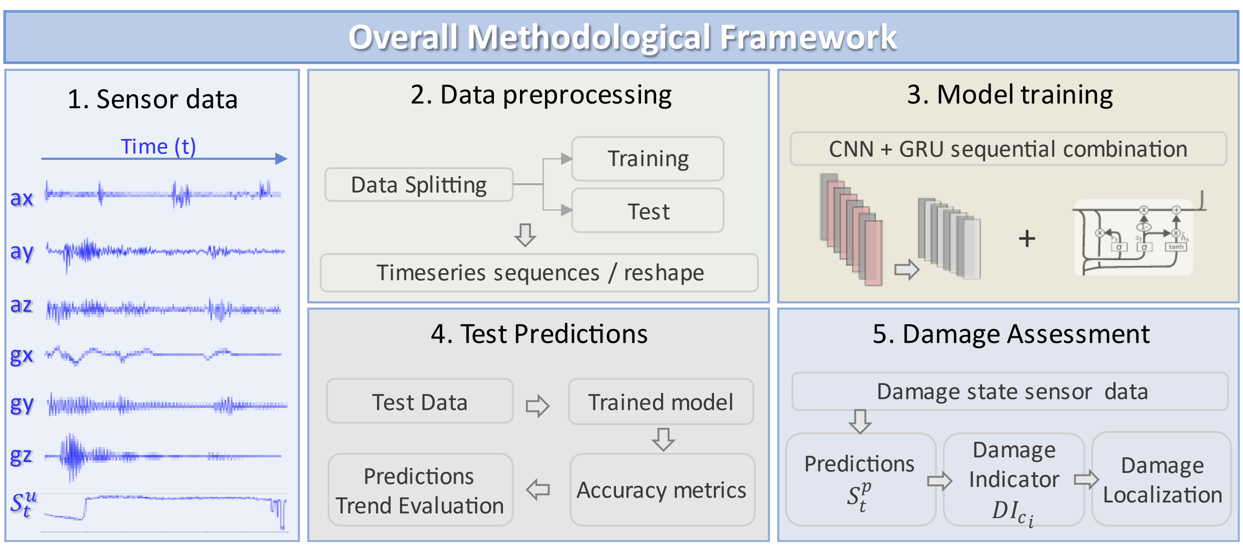


Figure 3-12. The overall methodological framework adopted in this study

In the proposed model architecture (section 3.2), the CNN model requires a "sequence window x number of training features" input shape. There are six input sensor signals representing the training features. For time series data, a sequence window must describe an event to be trained. In this case, we selected a sequence window of six timesteps representing a discrete event of MiC logistics. A sequence length that is too short may not fully incorporate the dynamics of the event. Meanwhile, a too-long sequence may contain a combination of events within one sequence, making it hard for the model to learn the features and correlations accurately. Meanwhile, a one-time step stride was fixed to incorporate a moving window over the whole time series.

3.4.1 Damage Assessment Framework

The proposed deep learning model for damage assessment follows a one-class anomaly detection approach. The model is trained for an undamaged module condition under different MiC logistic operations scenarios. The trained model then makes predictions for an undamaged module. So, any variations from the predictions should indicate the structural variations and, hence, structural damage. The deep learning model (M), given in the equation 3-9, considers the accelerometer and gyroscope readings at a specific time instance (t) and out the strain values (S_t^u) of an undamaged module component. The model trains a regression problem, considering six input variables: three directional acceleration (ax_t, ay_t, az_t) time series and rotations time series (gx_t, gy_t, gz_t). These input variables comprehensively represent the module motion during logistic operations and correspond to the consequent strain values (S_t^u).

After model training, the model is tested for its accuracy and performance. Accuracy metrics, consisting of mean square error (MSE), mean absolute error (MAE), coefficient of determination (R^2), and Pearson correlation, are evaluated. A trained model for the undamaged module can predict the strain values (S_t^p) for other observed variables

$(ax'_t, ay'_t, az'_t, gx'_t, gy'_t, gz'_t)$ at all the time instances (t) in new conditions. Thus, the difference between the predicted strain (S_t^p) and the undamaged strain (S_t^u) in the newly observed scenario, which represents the structural variations. The significant variation indicates the damage can be visualized in a comparison plot of strain. Moreover, root mean square error (RMSE) is a commonly used variation indicator for quantitatively evaluating the level of variation. The RMSE measures the average difference between a predicted strain (S_t^p) and the undamaged strain (S_t^u). Mathematically, it's a residul's standard deviation, as given in the equation 3-10.

$$M(ax_t, ay_t, az_t, gx_t, gy_t, gz_t) = S_t^u \qquad \text{Equation 3-9}$$

$$VI_{c_i} = \left[\sum_{t=1}^{N} \frac{\left(S_t^p - S_t^u\right)^2}{N}\right]^{1/2} \qquad \text{Equation 3-10}$$

$$DI_{c_i} = \frac{VI_{c_i} - \min\left(VI_{c_i}\right)}{\min\left(VI_{c_i}\right)}, \qquad \forall\ i \in 1,2,3,\dots,8 \qquad \text{Equation 3-11}$$

To determine whether the variation indication (VI_{c_i}) values are significant enough to indicate damage or evaluate the damage level; a comparative evaluation across the sensors installed at several locations on the structure is conducted. Such as the relative VI_{c_i} for each set of sensors installed at a corner (c_i) of a wall is calculated using Equation 3-11. The DI_{c_i} considers the lowest VI_{c_i} among all the sensor locations as a baseline and calculates the other DI_{c_i} relative to that. The critical corners of the structure having potential damage can be identified by comparing all the DI_c. Similarly, the difference between different DI_c also suggests the level of variation or damage level.

Further, a weighted average strain value approach is adopted to determine the potential damage location at each wall, following the principle of damage proximity near higher strain values [171,231]. Equations 3-12 and 3-13 provide the x_{d_W} and y_{d_W} cooridnates of damage location on each wall, by evaluating the average weights of DI_{c_i} at each corner with respect to distances x_i and y_i between the sensor installed locations on the same wall.

$$x_{d_W} = \frac{\sum_{i=1}^{N} DI_{c_i} . x_i}{\sum_{i=1}^{N} DI_{c_i}}, \quad \forall \ L \in \mathrm{LW, RW, BW, FW} \qquad \text{Equation 3-12}$$

$$y_{d_W} = \frac{\sum_{i=1}^{N} DI_{c_i} . y_i}{\sum_{i=1}^{N} DI_{c_i}}, \quad \forall \ L \in \mathrm{LW, RW, BW, FW} \qquad \text{Equation 3-13}$$

Chapter 4

RESULTS AND DISCUSSION

4.1 Analysis of Influencing Factors of MiC Logistics SC *(Objective I)*

4.1.1 Introduction

After a detailed review of the identified articles and factor extraction, the articles and factors were analyzed to investigate the different attributes of articles and factors' interrelationships further. The following section discusses the results of these analyses.

4.1.2 Scientometric Analysis

This section discusses the scientometrics of selected studies, such as publication trends, research domains, research focus, and the type of factors explored in each included study. The detailed scientometrics of 90 studies is presented in Appendix – A. The results highlight that the attributes of the selected studies sufficiently satisfy the research objectives of this study. Figure 4-1(a) shows the trend of publications over the years. More than 90% of the selected studies have been published in the last ten years. Most studies (25) were published during 2016-2019. Also, only seven studies were published before 2010.

Similarly, Figure 4-1(b) shows that most included studies (86%) are published in 53 journals. In contrast, only 14% of included studies are published in 8 conference proceedings. Such trends indicate that the selected literature sources are diverse, reliable, and up-to-date.

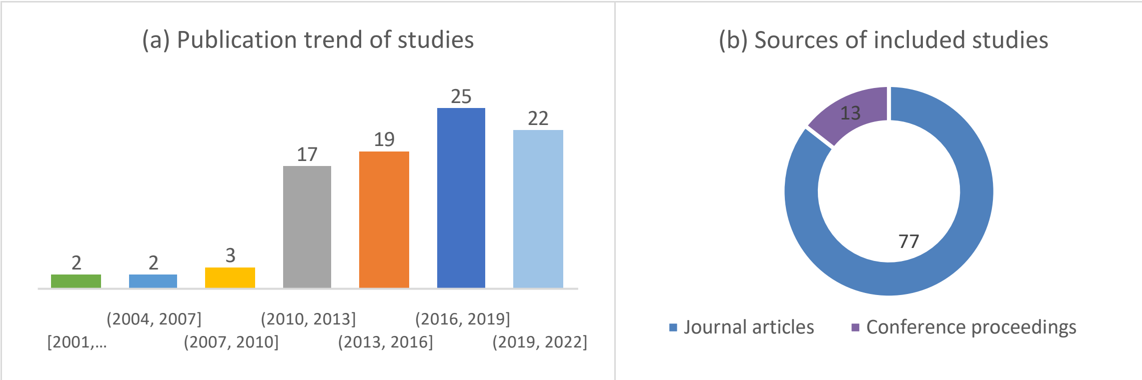


Figure 4-1. Distribution of selected studies by publication years and type of source

The research domains of the included studies are summarized in Figure 4-2(a). The final set of studies belongs to the domains of the general supply chain (64%), logistics management (19%), and modular construction (17%). The general supply chain domain contains the highest number of studies, as it is a seasoned and well-established research domain. In contrast, modular construction is a relatively new research domain; therefore, this domain contains only 15 relevant studies. In the modular construction domain, nine studies focus on MiC in Hong Kong and Malaysia, while the remaining focus is on prefabricated housing in other countries. Further, there is a vast amount of literature published in the logistics management domain, but only a limited number of studies (19%) could pass the eligibility criteria for this study.

Figure 4-2(b) shows the distribution of studies according to their research focus. The included studies concentrate on supply chain performance (28%), sustainability, and green supply chain (24%). Also, a significant number of selected studies focus on collaboration and third-party logistics (19%), which justifies the inclusion of the logistics management domain. Also, a few studies focus on a range of topics, such as information technology tools, knowledge management, risks, flexibility, agility, etc., highlighting the diversity of the included studies. Furthermore, Figure 4-2(c) summarizes the type of factors explored in selected studies. Most studies have listed the supply chain's influencing factors (54%) and success factors (37%), while the remaining studies explored the barriers or failures (6%) and risk factors (3%) for the supply chain.

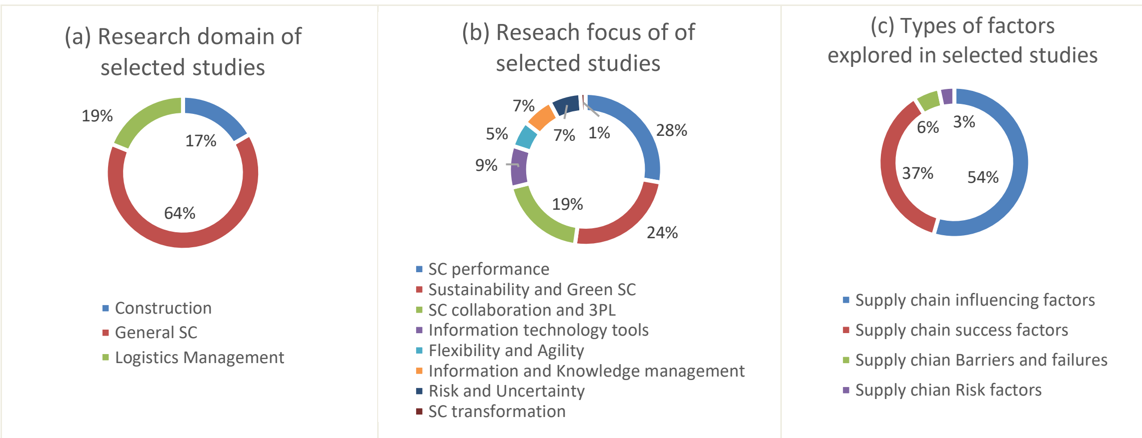


Figure 4-2. Research domain and research focus of selected studies

4.1.3 Ranking of MiC SC influencing factors

4.1.3.1 Weights of factors

Eigenvector weights are calculated to rank these factors. The overall eigenvector weights are shown in Figure 4-3(a). The 17 factors have eigenvector weights above the mean value (2.3%). The factor *promoting sustainability (SCM10)* has the highest weight (5.8%), followed by *communication and knowledge sharing with 3PL (IKS4)* and *robust SC (SCM1)*, both having 5.4% weight. A significant number of published studies promote sustainability factors to enhance the overall performance of the supply chain [199,274,326,351]. Similarly, in the supply chain management domain, some studies focused on the factors related to supply chain resilience [341], decisiveness [229], and flexibility [273], for a robust supply chain.

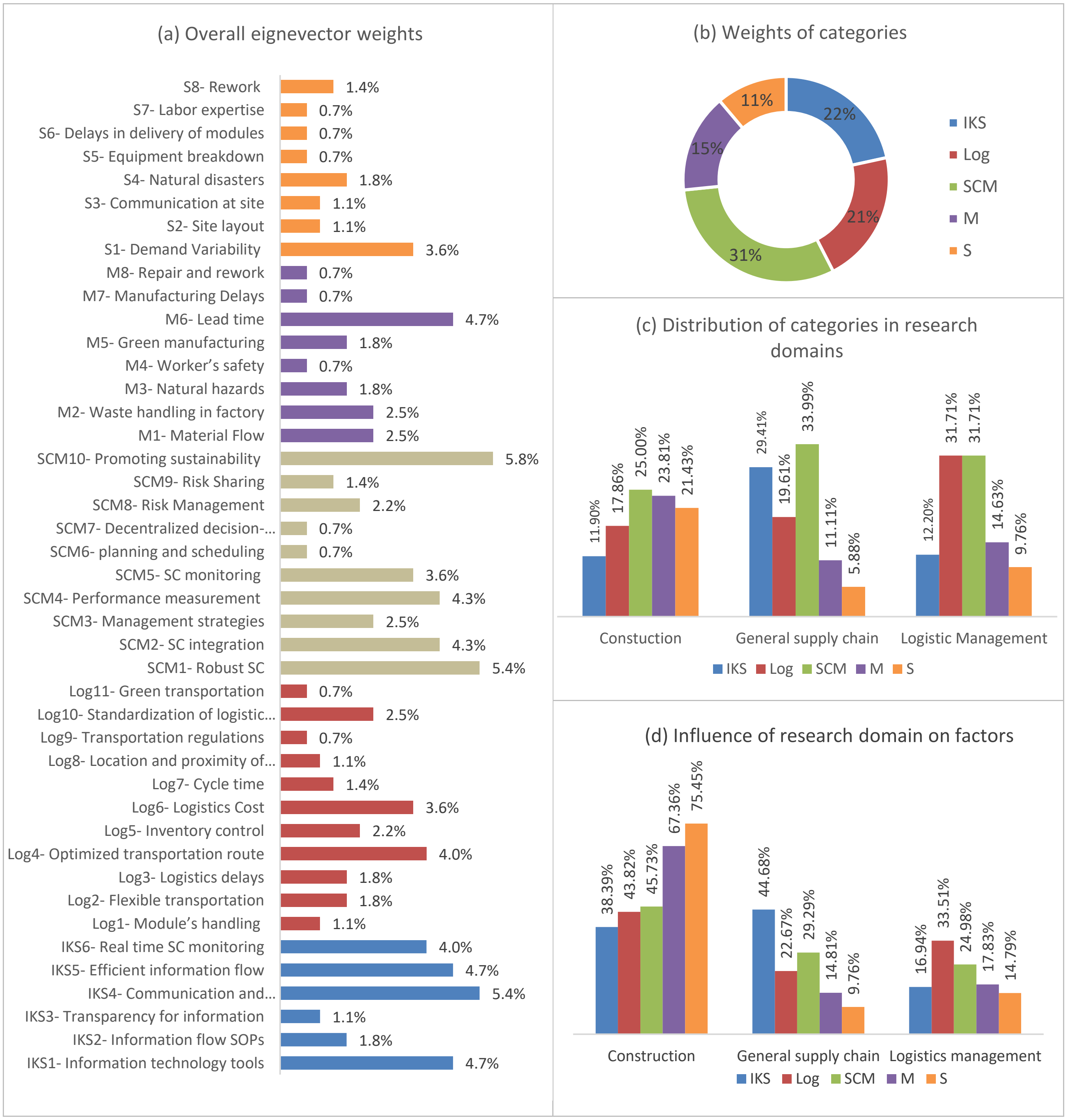


Figure 4-3. Eigenvector weights of factors and categories

Overall, there is little focus on the factors related to transportation, storage, manufacturing, and site delivery that influence supply chain performance. Such factors are more abundant in the studies related to modular construction [148,326,334]. A total of 10 factors have the lowest weights significantly (0.7%): *Log9, Log10, SCM6, SCM7, M4, M7, M8, S5, S6,* and *S7*.

4.1.3.2 Weights of factor's categories

Further, the overall importance of factor categories is analyzed by determining the eigenvector weights of each category. Figure 4-3(b) shows that the *SCM* category is the most critical (32%), whereas *logistics management* and *information & knowledge sharing* are moderately weighted, with 21% eigenvector weight. At the same time, the categories of *site delivery* (11%) and *manufacturing* (15%) have the lowest weights.

4.1.3.3 Distribution of factor weights in research domains

The distribution of categories' weights within the research domains is analyzed in Figure 4-3(c). These weights are calculated based on the factor's occurrences within each research domain. In the construction domain, the *SCM* category has the highest weight (24.7%), whereas *IKS* (11.2%) is the least weighted category. Similarly, in the general supply chain domain, *SCM* (35.26%) is the most weighted category, and *site delivery* (5.77%) is the least weighted category. In the logistics management domain, *logistics* and *SCM* both have the highest weights (31.7%), whereas *IKS* (12.2%) and *site delivery* (9.76%) are the least weighted categories.

4.1.3.4 Influence of research domains on factor categories

In Figure 4-3(d), fractional weights are calculated based on the factor's occurrence in each category per number of studies in each research domain. Estimated weights highlight the influence of the research domain in each factor's category. Results reveal that the construction domain primarily promotes *site delivery* (75.45%) and manufacturing (67.4%). However, *site delivery* factors are least promoted by the logistics management (14.79%) and general SC domains (9.76%). Similarly, the factors in *IKS* are promoted mainly by the general SC domain (44.68%) and construction (38.4%). Interestingly, *logistics* factors are most encouraged by the construction domain (43.82%), whereas the domain of logistics management (33.51%) is second. Similarly, *SCM* is primarily promoted by the construction domain (45.73%) instead of the general SC domain (29.29%).

4.1.4 Influence maps of factors – MICMAC Analysis

The MICMAC structural analysis is performed to map the influence relationships among factors (as explained in section 2.4.2). The top 33 significant factors are considered in MICMAC analysis. To improve the focus and quality of this analysis, factors with the lowest eigenvector weights (i.e., less than 0.7%) are excluded. Such factors occurred in less than two studies, thus deemed less relevant.

Firstly, direct influence analysis is performed using the 'MICMAC structural analysis software. The results are plotted on a direct influence map in Figure 4-4(a). Based on the level of influencing and dependence powers, the map is divided into four sections intersecting at the mean level [34]. The factors in section A have a strong influence and weak dependence power. Figure 4-4(a) shows this section has ten factors: Log1, *Log2, Log5, S2, S3, S8, M5, IKS2, IKS3*, and *SCM8*. Similarly, section B has three factors (*Log3, M3, S4*): strong dependence and strong influencing powers. The factors in section C have weak influence and strong dependence and consist of seven factors: *SCM1, SCM10, M1, M2, M6, Log4,* and *S1*. All remaining factors are laid out in section D. These factors are mostly disconnected from the system, as they have weak influences and low dependencies on other factors. Therefore, it is recommended that these factors be removed from the system. The direct influence analysis combines the factors' direct and indirect influences to determine the powers. For example, if A affects B and B affects C, A should transitively affect C. In this case, the direct influence analysis also counts the transitive influence. However, this approach undermines the minimum edge adjacency principle and the transitivity concept [5]. The indirect influence analysis deals with such issues and reduces the number of influencing factors in the system while increasing the system's sensitivity [259]. For conducting this analysis, the matrix power is increased iteratively. After two iterations, the stabilized results were achieved, which are presented in Figure 4-4(b). As a result, *SCM8* and *IKS2* are moved to section D from A, factor *Log2* is moved to section B from A, and factor *SCM2* is moved to section C from D.

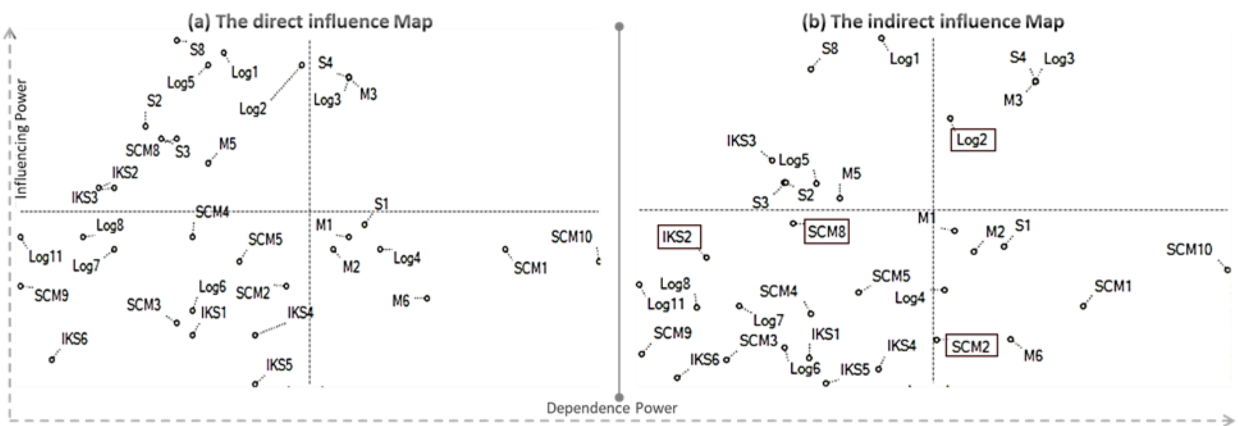


Figure 4-4. The Influence Map of MiC Supply Chain Influencing Factors

4.1.5 Themes of MiC Logistics Factors

The MICMAC analysis distributes the factors into four categories. For the semantic interpretation of these categories, it is vital to understand the intrinsic relationships and characteristics of a factor in each category. Therefore, the influential relationship among factors is discussed to understand their influencing mechanism over the MiC SC. Also, the factor's influencing and dependence powers are compared with the eigenvector weights and co-occurrence ratios (CoR). As a result, the logical interaction of identified themes is illustrated in Figure 4-5.

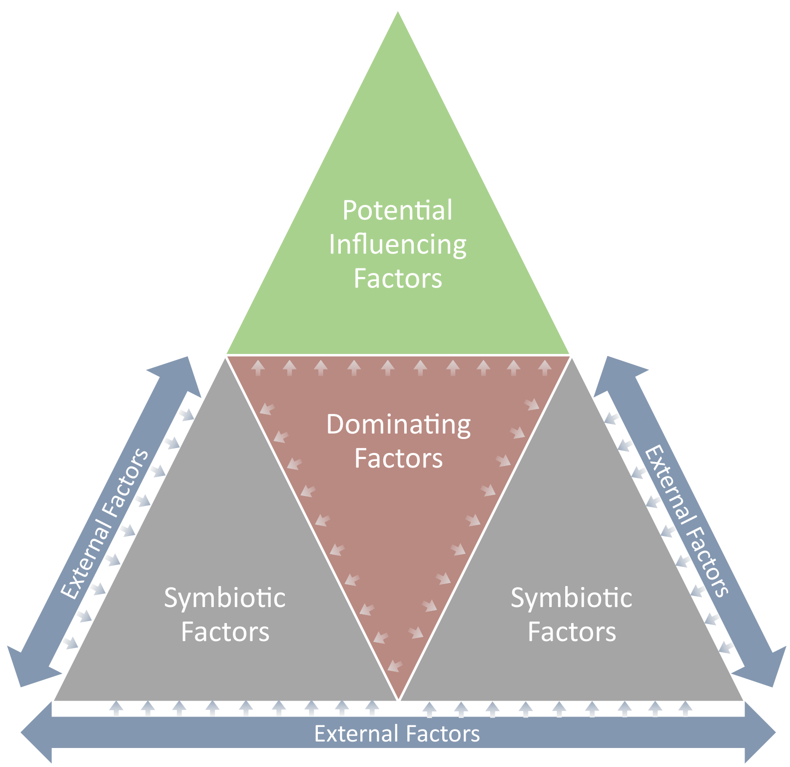


Figure 4-5 Illustration of factor's themes based on their relationship

The semantic terms for these themes are logically selected based on the influencing relationships among factors and categories. The "dominating factors" occupy the system's core while predominantly influencing the supply chain performance and indirectly impacting all other supply chain factors. On the other hand, the "external factors" are autonomous in nature and influence several other factors that affect the supply chain performance. The "symbiotic factors" are resultant or supportive factors that transmit the influence of other factors over the supply chain. Finally, the "potential influencing factors" are relatively new and require more research in the future to explore their influencing mechanism. Further details of these themes are discussed in the sections below.

4.1.5.1 Dominating factors

The factors in MICMAC section A are interpreted as dominating factors. These factors have a high co-occurrence ratio and influencing power, whereas their dependence is low. Such factors define the dynamics of the whole system of factors, as any change in these factors will have a snowballing effect across the system. Therefore, these factors can be considered input factors for the SC performance system. These factors are primarily focused on when making any decisions or strategies [62]. Figure 4-6(a) shows the critical relationship of dominating factors with other factors.

The *site layout (S2)* and *communication at site (S3)* would directly affect the assembling process of modules [148]. Any delay in assembling would halt all the previous supply chain segments. Similarly, *assembling reworks (S8)* would create critical delays and subsequently affect the whole supply chain, particularly in the case of JIT delivery of modules [148,205]. Also, it can be seen in Figure 4-6(a) that factors *site layout (S2)*, *communication at site (S3*), *assembling reworks (S8),* and *inventory control (log5)* are directly influencing the *lead time (M6)* [334]. Moreover, the factor *module's handling (Log1)* and *information transparency (IKS3)* are strongly connected with the *logistics delays (Log3)*. Similarly, *green manufacturing (M5)* directly influences *promote sustainability (SCM10)* [326].

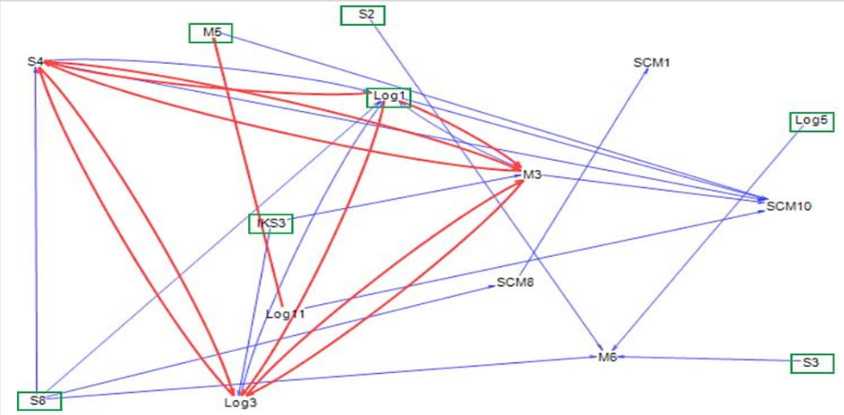
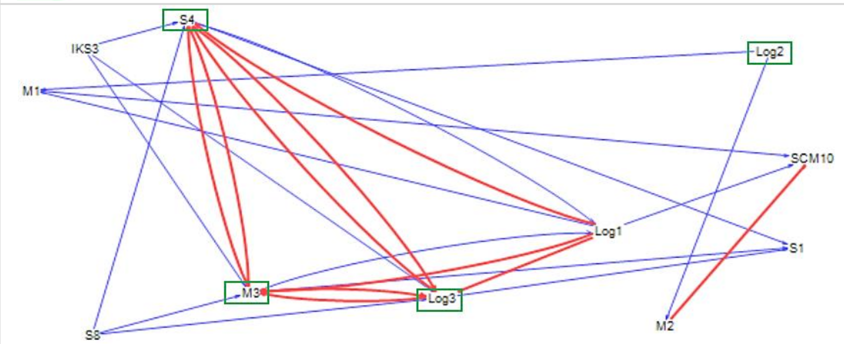
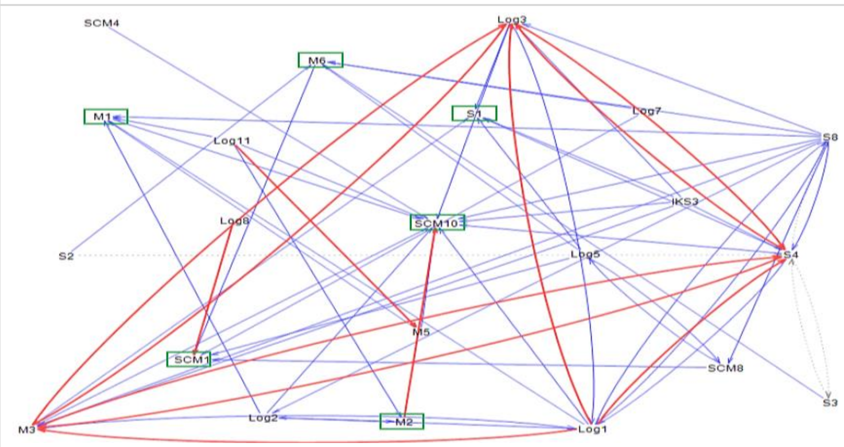
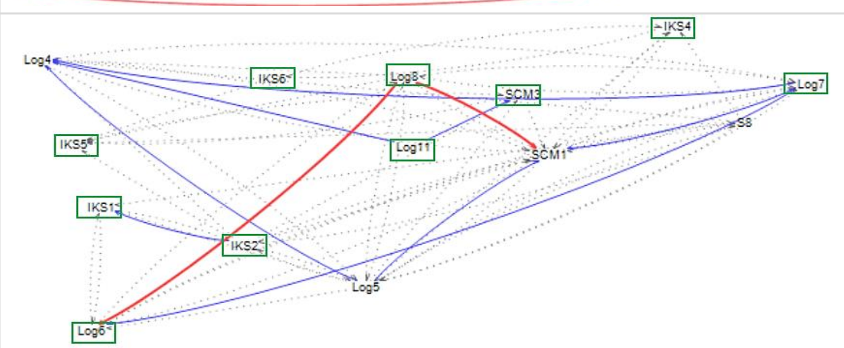
Factors			EV.	CoR	Relationship maps of factors
(a) Dominating factors	MICMAC Section – A	IKS3	1.1%	4.3	
		Log1	1.1%	6.3	
		Log5	2.2%	3.8	
		M5	1.8%	3.6	
		S2	1.1%	7.3	
		S3	1.1%	7.0	
		S8	1.4%	5.3	
(b) External factors	MICMAC Section – B	Log2	1.8%	4.8	
		Log3	1.8%	4.0	
		M3	1.8%	4.0	
		S4	1.8%	4.0	
(c) Symbiotic factors	MICMAC Section – C	SCM1	5.4%	2.0	
		SCM2	4.3%	2.0	
		SCM10	5.8%	1.8	
		Log4	4.0%	2.5	
		M1	2.5%	4.0	
		M2	2.5%	3.7	
		M6	4.7%	2.2	
		S1	3.6%	2.5	
(d) Potential influencing Factors	MICMAC Section – D	IKS1	4.7%	1.6	
		IKS2	1.8%	3.4	
		IKS4	5.4%	1.6	
		IKS5	4.7%	2.0	
		IKS6	4.0%	1.0	
		Log6	3.6%	1.4	
		Log7	1.4%	2.3	
		Log8	1.1%	3.3	
		Log11	2.5%	3.5	
		SCM3	2.5%	3.0	
		SCM4	4.3%	1.4	
		SCM5	3.6%	2.6	
		SCM8	2.2%	3.2	
		SCM9	1.4%	2.0	

Figure 4-6. Themes of factors based on their influential relationships
(EV: eigenvector weights, CoR: co-occurrence ratio)

4.1.5.2 External factors

The factors in section B are external factors. These factors have high influencing power and average cooccurring ratio. Factors in this theme directly impact the overall supply chain flow and indirectly influence the decisions related to other supply chain factors. External factors include *natural hazards (M3)*, *natural disasters (S4)*, and *logistics delays (Log3)*. These factors are related to the delays caused by the weather or other natural disasters. Such factors directly influence a supply chain's exposed activities, such as *material flow (S1)*, *module handling (Log1)*, and *assembling rework (S8)*. Therefore, external factors critically halt the whole supply chain [283]. However, according to the relationship map of external factors (see Figure 4-6(b)), factor *information transparency (IKS3)* can significantly help manage the impact of such external factors [298].

4.1.5.3 Symbiotic factors

Factors in section C having low influence, high co-occurrence ratio, and high dependence are interpreted as 'symbiotic factors.' The symbiotic factors predominantly exist in the presence of certain other factors, as they have high dependence. Such factors could be a (1) link in a cause-effect chain of other factors, (2) resultant of other factors, or (3) play a supportive role in snowballing the influence of other factors. Therefore, these factors may control and manage the overall dynamics of the system by reducing the negative impacts or enhancing the positive effects.

In Figure 4-6(c), the factors *robust supply chain (SCM1)* and *promoting sustainability (SCM10)* are highly dependent. These factors take the central position as resultant factors [271,349]. For example, *promoting sustainability (SCM10)* factor is primarily resulting from *efficient material flow (M1)* [87], *waste handling in factory (M2)* [20], *green* *transportation (Log11)* [351], *green manufacturing (M5)* [274] and *performance measurement (SCM4)* [263]. Similarly, the factor *robust supply chain (SCM1)* mainly depends upon *risk management (SCM8)* [341], *inventory control (Log5)* [148], and *lead time (M6)* [246].

4.1.5.4 Potential influencing factors

The factors in section D are realized as 'potential influencing factors.' These factors have weak influences and weak dependencies on other factors. It can be seen in Figure 4-6(d) that only *Log6* and *Log8* have significant influence; Most of the other factors in this theme are disconnected or have a fragile connection. The MICMAC analysis proposes to remove such factors as they have minimal impact, and their absence would not affect system performance [34,241].

In contrast, the eigenvector evaluation performed in this study suggests that most of these factors have significant importance. For instance, *IKS1, IKS4, IKS5, IKS6, Log6, SCM4,* and *SCM5* have above-average eigenvector weights. Despite high eigenvector weights, these factors have relatively low co-occurrences (CoR less than 2.0). This result suggests that these factors are mostly studied in separate literature. Also, some of these factors are relatively new in the literature and have a smaller footprint and low co-occurrence [193]. However, the literature suggests significant potential relationships between such factors to influence the MiC SC performance [88]. Consequently, the authors propose these factors as "potential influencing factors" that require more investigation in future research. The potential relationships among these factors are further discussed in Sections 7.4.1 and 7.4.2.

Logistics and SCM-related potential influencing factors

The relationship map in Figure 4-6(d) highlights that most of the potential influencing factors belong to the categories of *Logistics (Log)* and *Information and Knowledge Sharing (IKS)*. Among logistics-related factors, the *logistics cost (Log 6)*, *cycle time (Log7),* and *location and proximity of logistic facilities (Log 8)* are significantly related to each other [118,229]. The factory and storage locations can impact the delivery time and directly influence the overall logistics cost. Therefore, such factors play a crucial role in selecting 3PL companies [246]. The implication of cost and time in literature is mainly studied for *optimized transportation routes (Log 4)* [229]. The influence of cost and time over the other SC performance parameters is not discussed in detail. However, there could be potential implications, such as the *optimized transportation route (Log 4)*, *which* can help ensure *green transportation (Log 11)* by reducing fuel-based emissions [291].

The relationship map shows a significant relationship between *green transportation (Log 11)* and *Management strategies (SCM 3).* However, very little research is available to explain the supply chain's strategy for improving *green transportation (Log 11)* [351]. Similarly, *SCM*-related factors, such as *management strategies* (*SCM3)* and *SC monitoring (SCM5),* are primarily studied in isolation [28,103,148,243]. However, there is a potential relationship among such factors, which requires a more detailed investigation of their influencing mechanisms [298].

Information and knowledge sharing (IKS) related potential influencing factors

The factors related to *information and knowledge sharing (IKS)* are primarily discussed in independent studies, and their influence over other supply chain factors is rarely discussed [233,238]. However, Figure 4-6(d) shows some relationships between these factors (weaker links). For example, *information technology tools (IKS 1)* can ensure *real-time SC monitoring (IKS 6).* RFID is one of the most common technologies used for *real-time SC monitoring (IKS 6)* [317]. It can ensure module i*nventory control (Log 5)* by keeping a unique electronic record of each module.

Identifying the correct module and sequencing during logistics handling is a challenge in MiC SC. RFID technology can help to manage such challenges effectively. In addition, real-time information flow enables quick decision-making according to the latest status of SC flow. Further, the MiC assembling site is prone to uncertainties due to unpredictable events, such as assembling *reworks (S 8).* Such assembling site disruptions can affect the whole SC. In this case, *real-time SC monitoring (IKS 6)* provides additional control to manage the module flow and make critical decisions on time [317].

For a complex supply chain, *communication and knowledge sharing with 3PL (IKS 4)* are critical [217]. A multi-stakeholder, multi-mode, and multi-tier MiC SC is an information-intensive supply chain that acquires the continuous and *efficient information flow (IKS 5)* across the supply chain. The 3PL company holds critical information about transported or stored modules, such as location, module health, module type, delay time, etc. Such information is helpful at multiple levels for effective SC *performance measurement (SCM 4)* [294,304]. Moreover, effective *communication and knowledge sharing with 3PL (IKS 4)* can also provide opportunities to effectively implement innovative *management strategies (SCM 3),* such as Lean or JIT [148].

In a complex supply chain, information flow is also multi-stream and complicated, especially with advanced information technology, the information quantity increases. In such a scenario, information management is essential. The proper *information flow SOPs*

(IKS 2) should be implemented to ensure timely and correct information flow. In this regard, blockchain technology has been adopted to provide a secure and *efficient information flow (IKS 5)* across all the stakeholders in SC [56].

4.1.6 Summary (Objective I)

Multiple research domains are explored extensively to identify a comprehensive set of influencing factors. The critical factors are determined using a rigorous eigenvector weighting approach based on factors abundance in the literature. Moreover, the influence of factors on each other is studied according to their co-occurrence in the literature. Then, factors are classified based on their influence using MICMAC analysis. The interactions among factors are investigated, and the influence mechanism of factors is realized to propose themes of factors. The summary of all the analysis results for the top 10 factors is presented in Table 4-1.

The eigenvector-based ranking signifies the importance of factors based on the abundance of literature. However, it does not incorporate the individual interaction among factors and their strength of influence over the supply chain performance. Most top-ranked factors belong to the SCM category, as extensive literature has been published in this domain. The second most top-ranked factors belong to the information and knowledge management (IKS) category. Studies across all the research domains promote the information-related factors for an effective supply chain. However, MICMAC analysis results suggest that such factors have fewer connections with other SC factors. Generally, in the published literature, the factors related to the IKS and SCM are considered managerial. Therefore, past studies have mainly explored the interactions of these factors with administrative or organizational factors [193,233].

Table 4-1. Summary of analysis results

Rank	Top Ranked factors – Eigenvector weights	Most influential Factors – MICMAC	Most influential Factors – Combined analysis
1	Promoting sustainability (SCM10)	Module's handling (Log1)	Site layout (S2)
2	Robust SC (SCM1)	Assembling reworks (S8)	Communication at site (S3)
3	Communication and Knowledge Sharing with 3PL (IKS4)	Delays due to weather (S4)	Module's handling (Log1)
4	Lead time (M6)	Logistics delays (Log3)	Assembling reworks (S8)
5	Efficient information flow (IKS5)	Natural hazards at factory (M3)	Flexible transportation (Log2)
6	Information technology tools (IKS1)	Flexible transportation (Log2)	Information transparency (IKS3)
7	Performance measurement (SCM4)	Inventory control (Log5)	Logistics delays (Log3)
8	SC integration (SCM2)	Information transparency (IKS3)	Natural hazards at factory (M3)
9	Optimized transportation route (Log4)	Site layout (S2)	Delays due to weather (S4)
10	Real-time SC monitoring (IKS6)	Green manufacturing (M5)	Material Flow (M1)

On the other hand, the 'logistics' and 'site delivery' related factors are more influential for the MiC supply chain performance. For example, *module handling*, *flexible transportation*, and *inventory control* demonstrate strong influential relations with other supply chain factors. Similarly, the factors of site delivery, such as *assembling reworks*, *delays due to weather*, and *site layout*, are dynamically influencing the supply chain performance. It is because these factors occur at the supply chain's endpoint and control the flow, particularly in the case of JIT delivery. Moreover, factors related to natural causes, such as *logistics delays due to weather* and *natural hazards,* are autonomous and strongly impact the MiC supply chain performance. The top influential factors in the overall combined analysis are similar to the MICMAC analysis. However, their ranking is different.

The identified themes of factors based on the combined analysis conclude this study's findings and demonstrate the influencing system of factors. The dominating factors define the influencing system's dynamics as input variables, while the symbiotic factors control the influence of the dominating factors. The external factors are autonomous and cannot be controlled but are managed by improving the positive impacts of symbiotic factors. The potential influencing factors are abundant in literature but are primarily studied in isolation.

4.2 Exploring Technologies for MiC Logistics Supply Chain *(Objective II)*

4.2.1 Introduction

After the review of selected articles and identified technologies and their benefits, synergy analyses are performed to investigate the most suitable technologies and technology gaps further. The following section discusses the results of synergy analyses.

4.2.2 Synergies Between SC Technologies and MiC Challenges

To understand the application of technologies in different supply chains for a beneficial impact, we identified the chain of actions for each benefit of technology. The main purpose of identifying these chains of actions is to evaluate the features and capabilities of technologies for MiC logistics. For this purpose, we analyzed the extracted content from the text analytics. The developed chains of action are presented in Appendix – C. Following the chain of actions, we inferred the application of technologies for MiC logistics by establishing synergies between the benefits of technologies and the challenges of MiC.

The detailed table of synergies between each benefit of technologies and the MiC challenges is presented in Appendix – C and is further discussed in the following sections. The overall results of synergy analysis can be summarized in two ways: (a) how many technologies are responding to MiC challenges? and (b) how many MiC challenges each technology responds to? The overall summary results of synergy analysis are presented in Figure 4-7. The highest number of technology benefits, ten and nine, are found for the challenges "delays due to installation errors" and "communication and coordination among stakeholders, respectively. Whereas no identified benefit of technology is responding to the “module handling” and “local traffic management.” On the other hand, RFID, blockchain, and IoT respond to a maximum number of challenges, 13,8,8, respectively.

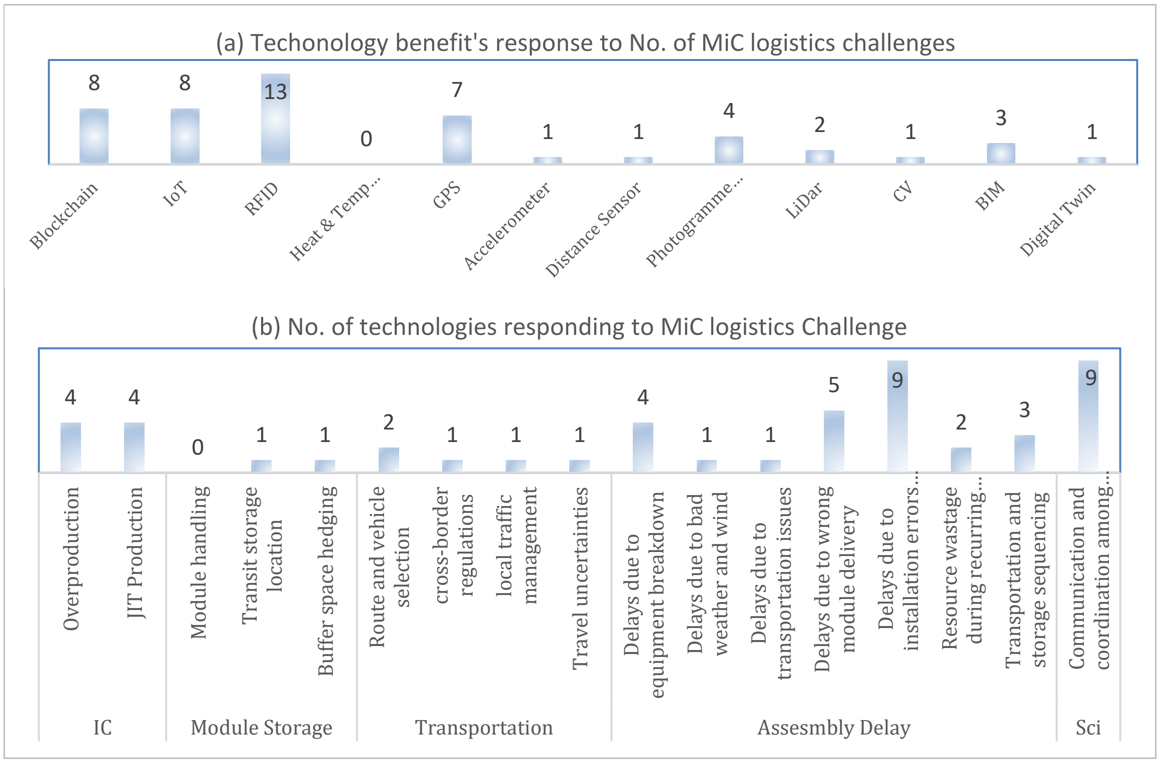


Figure 4-7. Overall results of synergy analysis

4.2.2.1 Blockchain for MiC logistics

Figure 4-8 below lists the benefits of IoT and sensors for several MiC challenges. Among these benefits, Enhanced security, trust, pseudonymity, transparency, and data integrity are most useful in dealing with (3) MiC challenges. For example, data security can reduce the chances of mislabeling modules and ensure correct delivery. Similarly, the trust and transparency of data will enhance the coordination among the stakeholders to improve the project's performance. Also, blockchain-based organized data can help better manage cross-border transit. Among other blockchain benefits, trustworthy information management and direct and real-time data access can improve stakeholder communication and coordination.

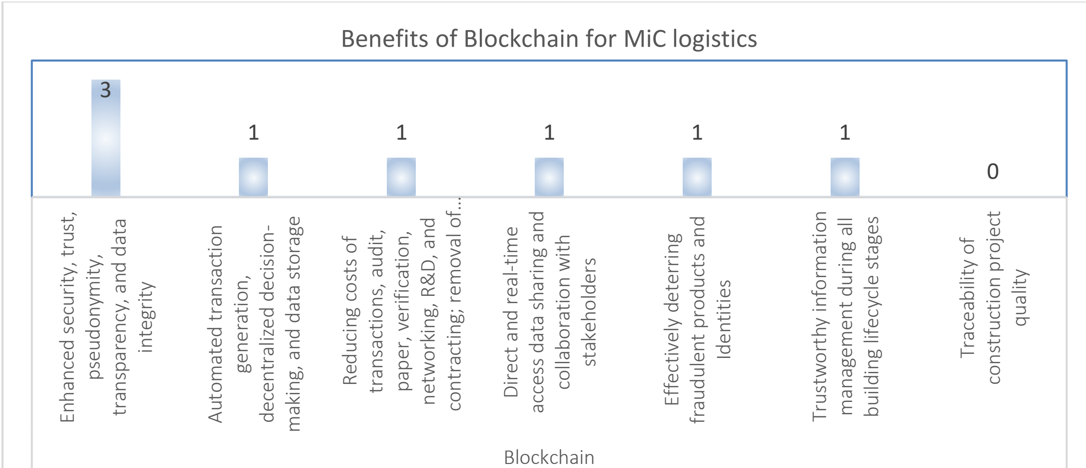


Figure 4-8. Blockchain benefits for MiC logistics.

4.2.2.2 IoT and sensors for MiC logistics

Figure 4-9 below lists the benefits of blockchain for several MiC challenges. Among these benefits, IoT has responded to most MiC logistics challenges. IoT is generally meant to implement real-time communications; thus, it can resolve several problems in any supply chain by enabling quick decision-making. Also, real-time communication improves the supply chain's agility; hence, the overproduction, storage, and Just-in-time (JIT) issues can be better managed for MiC logistics. Among sensors, the RFID sensor is found to be most impacting the MiC supply chain, as ten of its benefits are responding to 13 different MiC challenges, including correct module delivery, improving the safety during assembling, warehouse management, tracking the delivery, etc. GPS tracking also supports MiC logistics by improving delivery tracking, route optimization, and managing JIT delivery at the site. Other sensors are being used in different supply chains; however, they don't add value to MiC logistics for the same benefits.

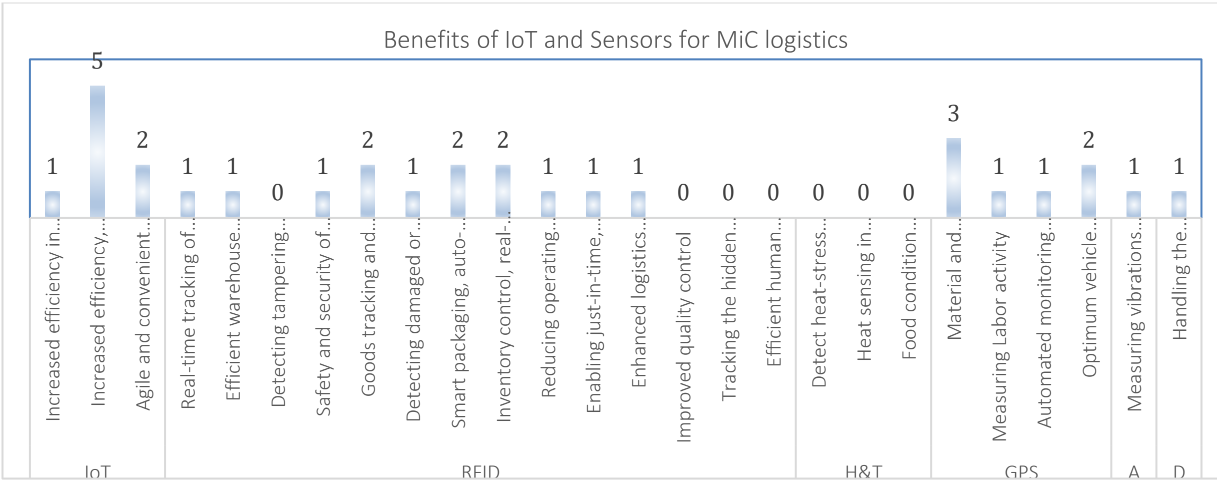


Figure 4-9. IoT and sensors benefits for MiC logistics.

4.2.2.3 Photogrammetry for MiC logistics

Figure 4-10 below lists the benefits of photogrammetry for several challenges of MiC. Most of these benefits are useful for construction site operations and thus can improve MiC operations. However, the literature does not report their direct value for logistics operations. From their benefits, we noticed that photogrammetry could be used to monitor the quality of manufactured modules and compare the module's condition after logistic operations, as LiDar and computer vision approaches can detect cracks or damages to some extent. Therefore, comparing pre and post-logistic models can reveal the potential damages that occurred during the transportation and handling of modules.

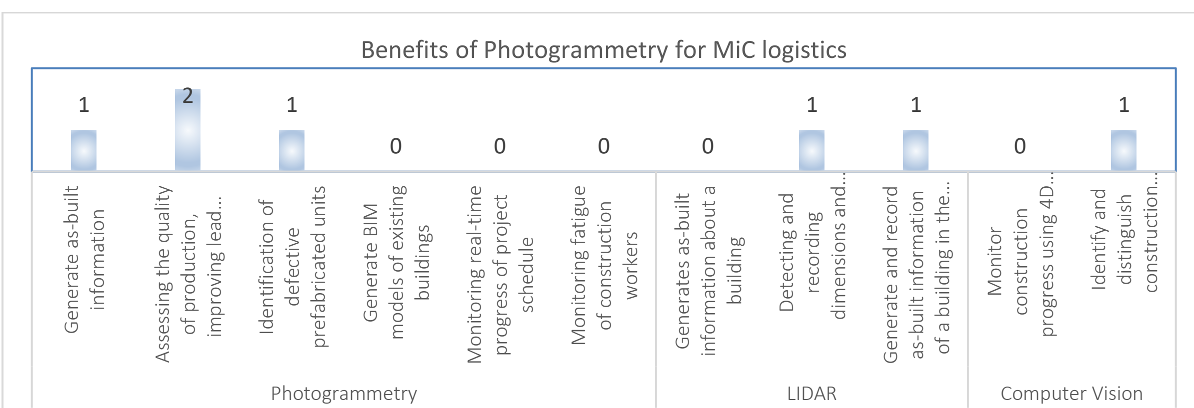


Figure 4-10. Photogrammetry benefits for MiC logistics.

4.2.2.4 BIM and Digital Twin for MiC logistics

Figure 4-11 below lists the benefits of blockchain for several MiC challenges. Among these benefits, Despite a wide range of BIM applications and benefits in the supply chain, it does not directly respond to particular MiC logistic challenges. However, its application for site management helps monitor the MiC assembling operations to support logistic-related challenges. Also, collaborative data management in BIM can help supply chain actors collaborate easily and quickly to changes. Similarly, Digital Twin is a powerful supply chain tool but has found less response towards MiC logistics challenges. However, its capabilities offer a great deal for overall MiC logistics management.

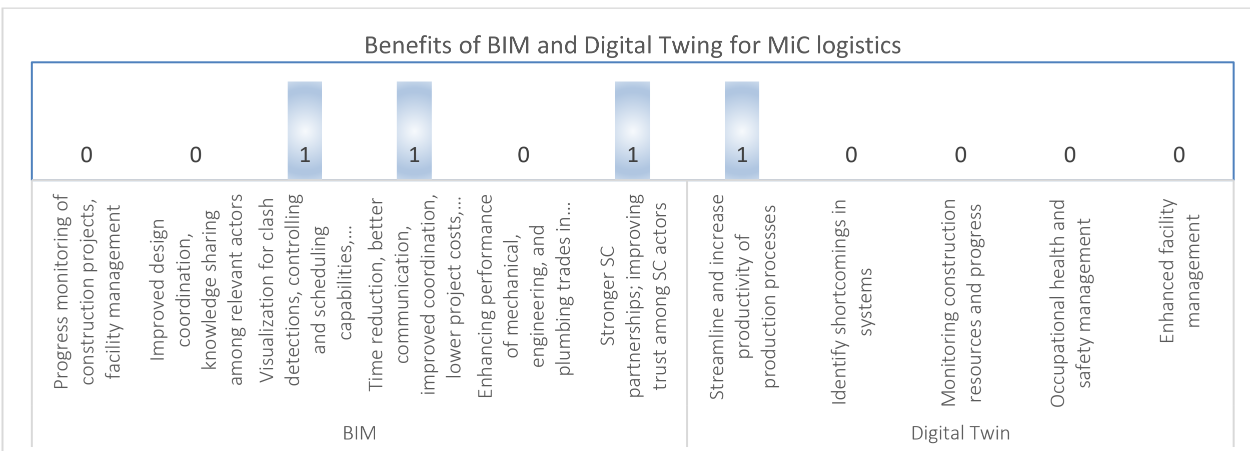


Figure 4-11. BIM and Digital Twin benefits for MiC logistics.

4.2.3 Most Influential Technologies and Technology Gaps

Following the detailed discussion, the overall synergy analysis results are summarised as (a) influential technologies – the technologies responding to most MiC challenges and (b) technology gap – the MiC challenges least addressed by technologies.

Figure 4-12 highlights the most influential technologies for MiC challenges. RFID, IoT, Blockchain, and GPS are among the most influential technologies for MiC logistic operations, responding to the highest number of challenges, 13, 8, and 8, respectively. These technologies support real-time tracking and improve communication, the most promoted interventions for integrating the supply chain segments and improving performance [84,161,164,191]. These technologies primarily respond to the MiC logistic challenges related to transportation and supply chain coordination [78,84,191]. Also, these technologies are comparatively more developed, and their application has been widely reported in different supply chains [21,85,164,338].

Although BIM and digital twins offer significant functionalities and capabilities, their applications are limited and only respond to four MiC challenges. These critical challenges include equipment breakdowns and enhanced coordination among stakeholders. BIM and digital twin provide platforms for managing the detailed data related to project and module structural attributes [85,216]. These features enable stakeholder collaboration for swift decision-making and progress monitoring and facilitate tracking the variations in modules' structural attributes [31,173]. Also, the visualisation capabilities of such technologies can simulate real-time supply chain operations to improve the productivity and safety of MiC logistics [159,183].

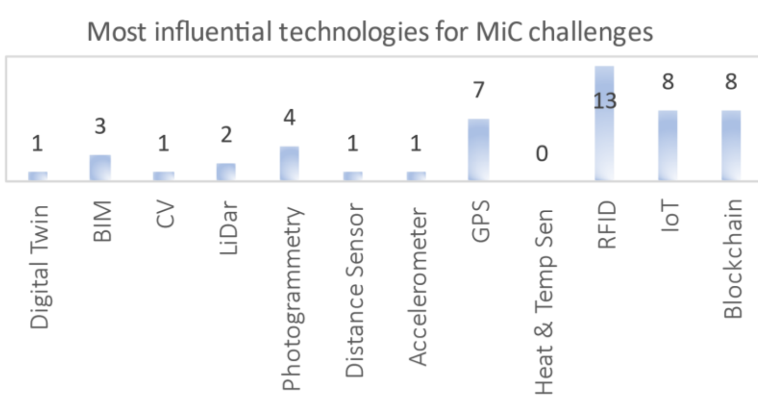


Figure 4-12. Most influential technologies for MiC Challenges

On the other hand, Photogrammetry, LiDar, and computer vision offer promising benefits. These technologies can help monitor the MiC structural variations during logistic operations, thus helping to reduce the delays due to installation errors and damage repair. LiDar and computer vision technologies can help assess the manufactured quality of the built module [69,236,280]. As well as they can be used to measure geometrical and surface defects at any point [125,344]. Similarly, accelerometers and distance sensors show potential benefits by tracking the precise module motion tracking during MiC logistics operations. Thus, these sensors can help improve the module's structural safety by monitoring the impacts and avoiding clashes. However, such applications for MiC logistics need further evaluation, as the literature lacks such studies.

The technology gaps and most addressed MiC challenges are highlighted in Figure 4-13. The most addressed challenges associated with nine different technology benefits are the 'communication and coordination among stakeholders' and 'delays due to installation errors'. These technologies mainly benefit from real-time communication and tracking to handle uncertain situations, such as IoT, RFID and blockchain, which are the most influential technologies. It is important to note that such technologies do not offer any support to avoid events like 'installation errors'. Instead, they manage the event after it occurs through improved communication and coordination.

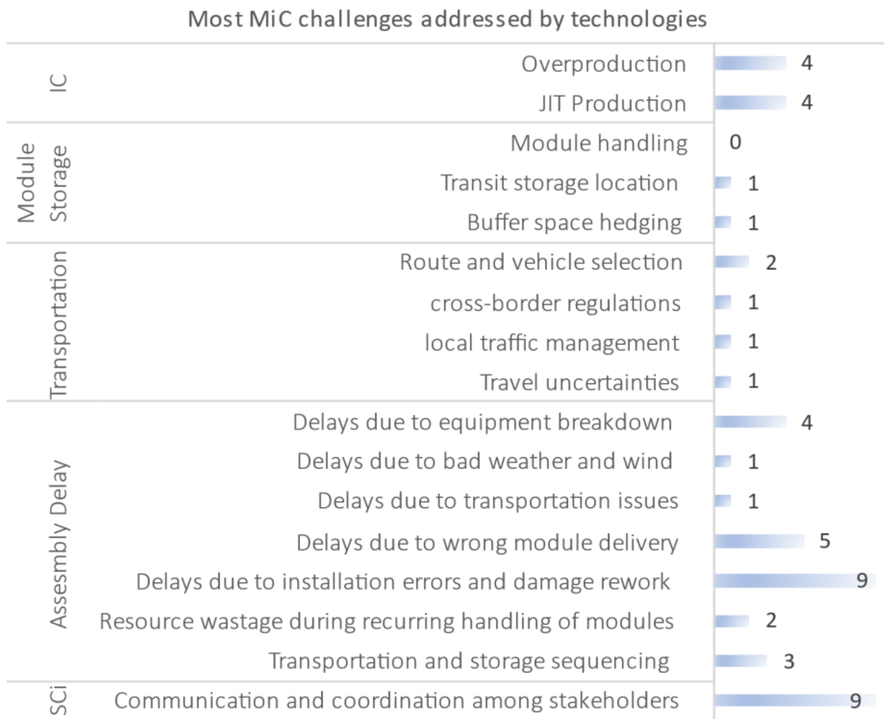


Figure 4-13. Technology Gaps for MiC Challenges

The MiC challenges, such as overproduction, JIT production, equipment breakdown, module sequence and wrong module delivery, have strong technological support in the form of blockchain, RFID and IoT. Many of these technologies' benefits can handle such challenges effectively and help improve the associated MiC supply chain operations. Other challenges like optimum transit storage location, managing cross-border transit regulations, delays due to equipment breakdown, and travel uncertainties have partial support from some technologies. Some of the technology capabilities are suitable for managing these challenges; however, these challenges have not yet been applied to handle these challenges. Thorough frameworks are still needed to use these technologies to manage such challenges properly.

There is a critical technology gap for MiC challenges' module handling'. This challenge involves vital issues during the storage and stacking of modules, such as module structural deformation, damages and overall structural health. Such critical issues can further trigger other challenges of MiC logistics, such as 'delays due to installation errors and damage repair'. Also, any accident during module handling can lead to hidden structural damage, which can cause a severe safety hazard and require additional repair time before assembly. Therefore, this gap requires critical technological attention.

4.2.4 Proposed Technology Framework

Considering the functional benefits of technologies, an integrated technology application framework is proposed for the most neglected challenge of MiC logistics, 'module handling'. As presented in Figure 4-14, the framework integrates IoT sensors, LiDar, computer vision, and digital twin technologies to monitor the impact of logistic operations, including module handling, on the module structure. This integrated technologies application can help improve logistic operations' productivity and safety and monitor the module's structural health. A manufactured module will be scanned using a LiDar, and computer vision can further process this scan to reveal the module's structural attributes, such as alignment and material finishes, to assess the manufacturing quality. Such pre-logistics scanned information, along with other structural properties and attributes, will help to develop an initial digital twin of all the modules.

In the second stage, the technologies for real-time logistics monitoring include IoT sensors, such as accelerometer, tilt, distance measurement, and temperature and moisture sensors. These sensors can monitor the MiC module's motion in real-time during module handling, such as loading and unloading, storage stacking, and transportation. Thus, these sensors can provide real-time motion data to the digital twin and enable the 3D simulated visualisation of any logistic operation, improving the safety and productivity of these operations. Meanwhile, the distance sensor can initiate an immediate warning before any collision. Also, real-time motion data can help estimate the impact level during any accident or collision, – providing early information about potential damage, – and reducing the delays due to inspections and damage reworks.

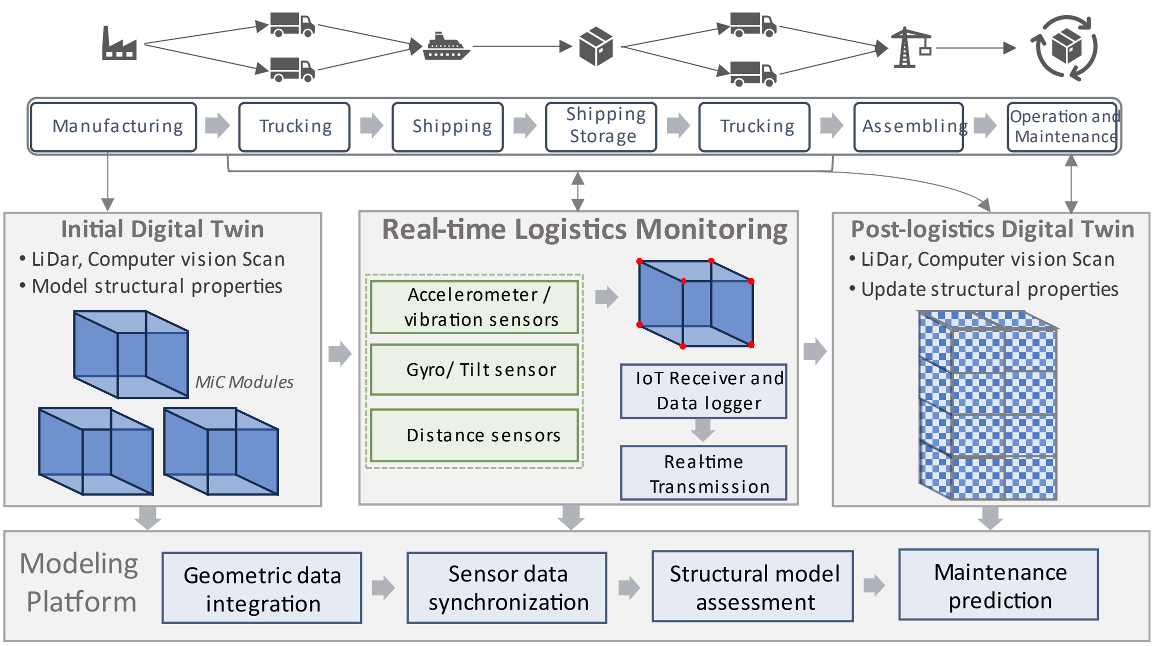


Figure 4-14. Application of technologies for MiC module structural safety and health during logistics

Additionally, such real-time motion data can be used with advanced structural modelling, such as Finite Element Methods (FEM) or with deep learning models to predict the changes in the module structure that may lead to any crack or damage in future. Such assessments can help develop proactive maintenance plans and improve the overall structural life of MiC buildings. To aid this, a post-logistic digital twin update using LiDar and computer vision can be performed to assess any structural variations during logistic operations. The comparison of initial and post-logistic digital twin will help assess the overall structural health deterioration during the logistics. Also, it can help reduce manual module inspections and facilitate module alignment before assembly.

4.2.5 Summary (Objective II)

The study contributes to the body of knowledge by identifying the MiC supply chain challenges, critical Supply chain technologies, and their benefits and drawing synergies between the technologies' benefits and MiC challenges. A powerful text analytical approach helped to effectively investigate the vast literature and identify the use and benefits of supply chain technologies. RFID, IoT, GPS, and Blockchain technologies are among the most popular technologies in supply chain studies. These technologies also address some of the MiC logistic challenges. For example, communication and coordination among supply chain stakeholders, delays due to installation errors, equipment breakdown and wrong module delivery, JIT delivery, etc.

On the other hand, some technologies are not being used to utilize their full potential in resolving supply chain issues. For example, tools like BIM and Digital Twin have vast capabilities to manage and organize multi-spectrum information at all levels of the supply chain. Thus, such tools can address several critical supply chain challenges. However, existing studies lack research on adopting such tools to address the most vital challenges. Similarly, several MiC challenges got limited attention and support from technologies, such as delays due to transportation issues, module handling, travel uncertainties, buffer space hedging, etc. The proposed framework incorporated technologies with vast potential to address several unattended MiC supply chain challenges comprehensively.

4.3 Developing a Multi-Sensing IoT System for Monitoring the MiC Module Structure

(Objective III)

4.3.1 Introduction

In this study, (1) a smart wireless sensing system is developed that adopts microsensing technologies, integrates them in a compact small device that can be easily installed on a module, and enables IoT-based communication. (2) The developed system is tested and calibrated to ensure high precision and accuracy. (3) A field experiment demonstrates its detailed application for real-time damage assessment and health monitoring of the MiC module during logistics operations. The following section discusses the development of the IoT sensing system and its demonstration with a field experiment.

4.3.2 Developing IoT sensing system

The standard IoT system's architecture consists of three essential layers, as shown in

Figure 4-15 [196]. The first perception layer is the IoT physical node, which consists of intelligent sensors that gather the required information. The second network layer is the active communication layer, which transforms the physically sensed information into organized and logical information and transmits it. This layer stores and processes the received data, presenting it in more logical knowledge for the application.

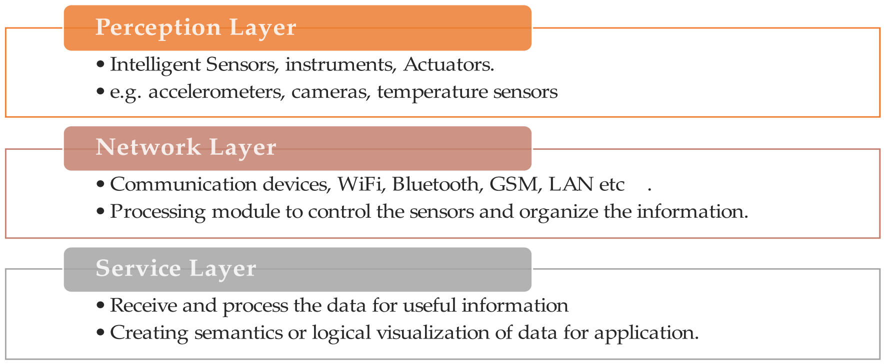


Figure 4-15. The basic IoT architecture

Following this IoT architecture, the developed system comprises peripheral sensing units (SU) and a central communication unit (CU) representing the perception layer and network layers of IoT, respectively. The peripheral sensing units are small integrated sensing devices installed over the MiC module structure, as shown in

Figure 4-16. These units monitor the structural strains, acceleration, and tilt angle at several points on the structure. Each peripheral unit is wirelessly synced with the CU and sends real-time data. The central communication unit (CU) then processes all the received data from all the installed SUs, stores data backup, and transmits it to a web server. Further particulars of the developed system are detailed in the following sections.

(a) Peripheral Sensing Unit (SU) (b) Central Communication Unit (CU)

Figure 4-16. Developed IoT sensing system.

4.3.2.1 Peripheral Sensing Unit

The design rationale for the peripheral sensing unit (SU) is based on practical constraints during MiC logistics and building use phases. Each MiC module needs several SUs for effective monitoring of structural performance; hence, a large number of SUs are required for the whole building. Thus, the development cost for SUs is primarily focused, and cheaper available components are utilized. Further, the form factor of SU is kept minimal, making it practically invisible when installed in a module, thus avoiding any interference to or from the building occupants. First, a double-sided printed circuit board (PCB) was designed to ensure a minimum form factor for SU development. The components, microcontroller (MCU), accelerometer, gyroscope, strain gauge analog-to-digital converter (ADC), wheatstone bridge, battery, and some connectors, are mounted on the designed PCB for manufacturing the SU.

The Xiao ESP32S3 is used as an MCU to control IMU and ADC functions and further process the data. The Xiao ESP32S3 is a tiny but robust MCU offering a 240MHz 32-bit LX7 dual-core processor, enabling enough computational power to handle complex machine-learning models as well. It supports integrated 8M PSRAM & 8MB Flash, WiFi 2.4, and Bluetooth 5.0 while consuming 108mA power at peak performance and 14μA in sleep mode. The LSM6DS3 inertial measuring unit (IMU), containing an integrated 3-axis accelerometer and gyroscope sensors, is used. It's a high-performance, low-noise IMU that consumes 0.42-1.25 mA power while measuring up to ±16g acceleration and ±2000 dps angular/ rotational speed [24].

An HX711 ADC is utilized to read signals from two strain gauges. HX711 is a two-channel ADC widely used as a load cell and is a cheaper alternative. This 24-bit signal amplifier converts the strain signal from strain gauges to digital values (0 - 1023) [284]. A four-wire whetstone bridge configuration is required to connect a strain gauge to the ADC. Quarter wheatstone bridges are configured for each strain gauge, connecting a strain gauge and three 120-ohm resistors in series.

Moreover, to reduce the current noise and improve the sensor readings, three 100nf capacitors are connected to each component. The JST Ph2.0 connectors are used to connect the detachable strain gauges and battery. A 1200mAh lipo battery is attached to the circuit and placed in a compact case. The battery capacity can be enhanced depending on the requirements. The overall size of the sensing unit is around 35x35x15 millimeters, and it weighs about 160 grams.

The SU firmware is programmed using the Arduino IDE. ESP-NOW wireless communication protocol is employed in firmware for data transmission between SUs and CU, enabling peer-to-peer communication. ESP-NOW is highly suitable for continuous data transmission scenarios as it offers low latency and consumes significantly low power for peer-to-peer communication [94].

4.3.3 Central Communication Unit

The CU is the central unit that connects to all the peripheral units. It can monitor and control the SU's functioning, such as battery status, switching to low power mode, activating/deactivating any sensor, and requesting data transmission. The primary function of CU is to collect sensor data from all the SUs and transmit that to the server. A built-in module was used to develop CU, which integrates ESP32 MCU, SIM7600 cellular module, GPS, SD, and WiFi. The CU is also equipped to support large-capacity lipo batteries and solar charging to enhance its portability. A mini OLED display is attached to the CU to monitor the status of connected SUs and control other functions. ESP32 MCU processes the received data from all the SUs, indexes the data streams, and stores it in the built-in SD card module as a backup. Meanwhile, the SIM7600 module enables real-time data transmission using a 4G internet network, ensuring seamless transmission from remote areas and sites where the availability of WiFi could be an issue. The sensor data communication and storage framework is elaborated in Figure 4-17.

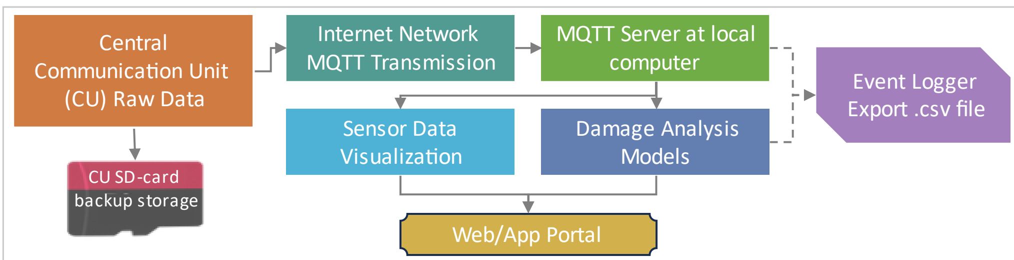


Figure 4-17. Sensor data communication and storage framework

The CU firmware programming employs the MQTT (Message Queuing Telemetry Transport) protocol for cellular network transmission. MQTT is highly suitable for IoT-based and high-latency networks as it offers lightweight, asynchronous data transmission and can retain the messages in the queue [350]. An MQTT-based server is established on a local computer to receive and log the data. The logged data is conveniently accessible through .txt, .csv, or Excel file formats for further processing and analysis. Additionally, the web server publishes the incoming data's real-time plots to monitor the data visually. Meanwhile, the damage analysis algorithms are programmed in Python, which accesses the sensor data from the server and publishes the results on the web portal.

4.3.4 IoT Sensing System Performance Testing and Calibration

Different tests and calibration are conducted to ensure the developed sensing system's accuracy. The following section explains the evaluation process and results.

4.3.4.1 Performance testing

For performance testing, the SU was placed in a relatively static environment where 5-meter surroundings were restricted to avoid external interference. The readings measured in a static environment represent the noise in the accelerometer and gyroscope, shown in Figure 4-18(a, b). The 100-minute measurements show that acceleration noise in the ±2g sensing range has a root mean square error (RMSE) of 0.01, mostly between 0.02 to -0.02g. Similarly, the gyroscope has an RMSE of 0.0023, ranging between 0.003 to -0.003 rad/sec. Considering the non-ideal static environment conditions, these results are reasonably comparable with the standard specifications of LSM6DS3 IMU [24]. In addition to the noise, there is another inherent limitation of any gyroscope, called a Turn-On Bias [68]. When a gyroscope is switched on, there will be unstable measurements initially, causing drift and offset [39]. It can be seen in Figure 4-18(b) that the gyroscope measurements show some drift in the beginning. To deal with this bias, the SU is programmed to record the unstable measurements at startup and then reduce offset based on initial unstable readings. Thus, the remaining measurements become stable, and the offset is reduced to 0.001 rad/sec. Such a minor offset in angular velocity measurements does not affect the relatively calculated rotations and angles.

Further, the strain gauge measurements were tested against temperature variation. For this purpose, the SU was placed in a room where a 24°C ambient temperature was maintained. When SU starts, its components (mainly MCU) generate heat due to continuous operations.

This heat causes the overall device temperature to rise above ambient temperature until a balance between ambient temperature and heat dissipation is reached. The time to achieve such a balance is critical for strain measurements, as strain readings are highly sensitive to temperature variations, as shown in Figure 4-18(c). The SU temperature kept growing for the initial thirty minutes and caused the strain values to drift despite no external load being applied. The drift in strain measurement was stopped after the balance between ambient temperature and device heat dissipation was reached, and the temperature was sustained at 36°C. Similar to the SU's internal heat dissipation, in real-world scenarios, variations in the surrounding temperature can also cause disruptions to the strain measurements.

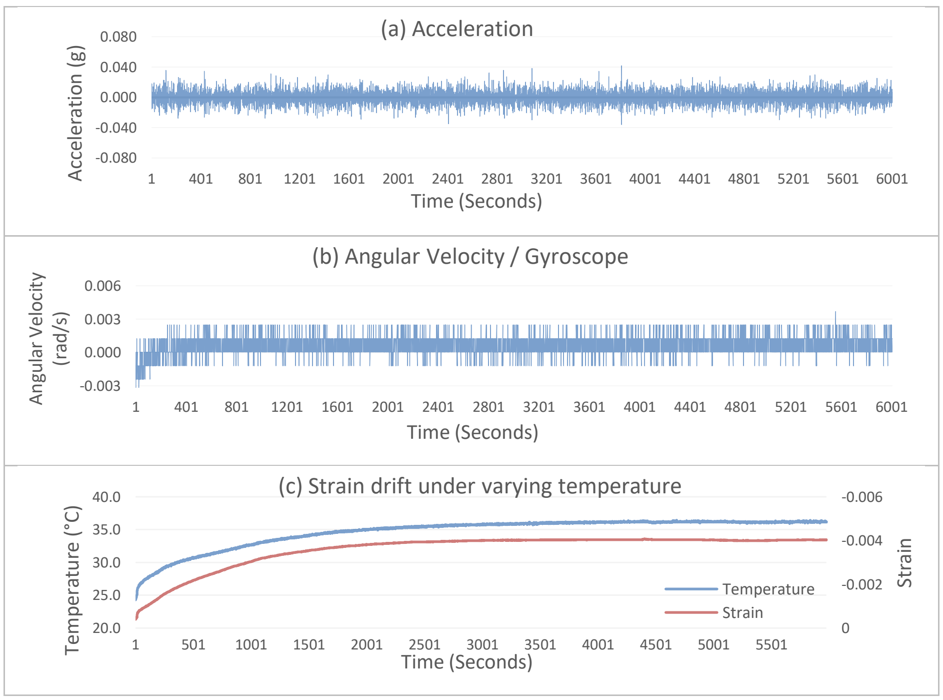


Figure 4-18. IoT sensing system performance tests under static conditions.

Temperature Compensation

A model to compensate for the effect of temperature variation is developed to deal with the strain drift issue. The drifted strain values were measured against the varying temperature (24-36°C) for 100 minutes. The setup was ensured to be static and vibration-free so that the actual strain remained zero. Then, a second-degree polynomial regression model of drifted strain against varying temperatures was developed, as shown in Figure 4-19(a). The coefficient of determination (R^2) for the regression model is 0.9397. This regression model gives the calibration factor to further calculate the actual strain values (Sa), as given in Equation 4-1, where S_d is the drifted strain, and x is the temperature. The actual strain values for this test were calculated using this calibration model and are shown in Figure 4-19(b). It can be seen that the resultant actual strain values have no drift and are now closer to zero, with RMSE 0.000254με.

$$S_a = S_d + 0.000006x^2 - 0.00008x - 0.0011 \qquad \text{Equation 4-1}$$

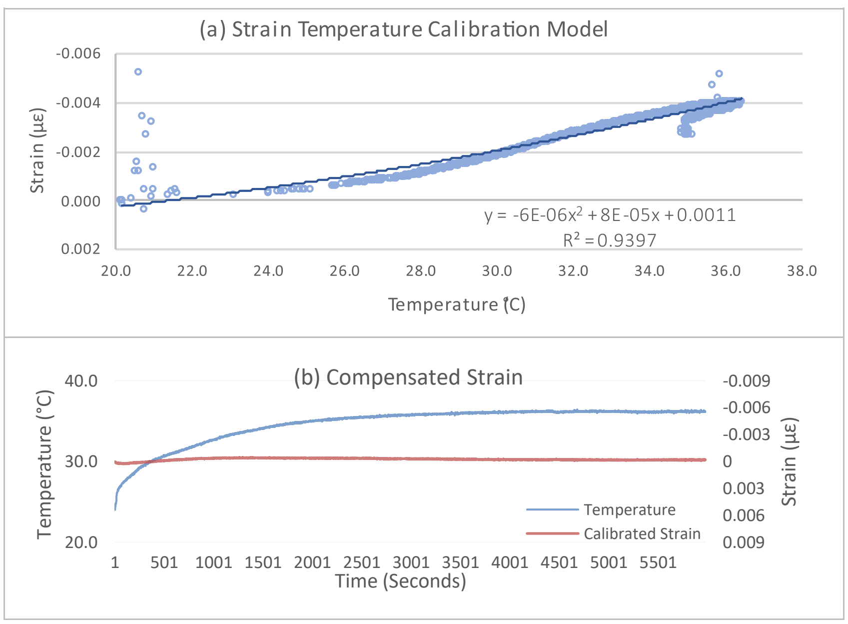


Figure 4-19. Strain drift and temperature affect compensation.

Performance comparison with UTM

Finally, the accuracy of SU is tested by comparing its results with a standard universal testing machine (UTM). For this purpose, a compression test under cyclic loading on a concrete block is conducted (Figure 4-20(b)). The strain gauges connected to UTM and SU were installed on opposite sides of the concrete block (Figure 4-20 (c)). The test results in

Figure 4-20(d) show that SU and UTM strain gauges show minor differences in strain values, with just 0.005με RMSE. Then, the concrete block started developing cracks on the SU strain gauge side after 2nd cycle of loading (115 seconds). After five loading cycles (300 seconds), the major crack failure occurred, visible in both SU and UTM strain values. Overall, test results showed promising performance of SU strain measuring, with 0.011με RMSE, despite early cracks on the SU strain side.

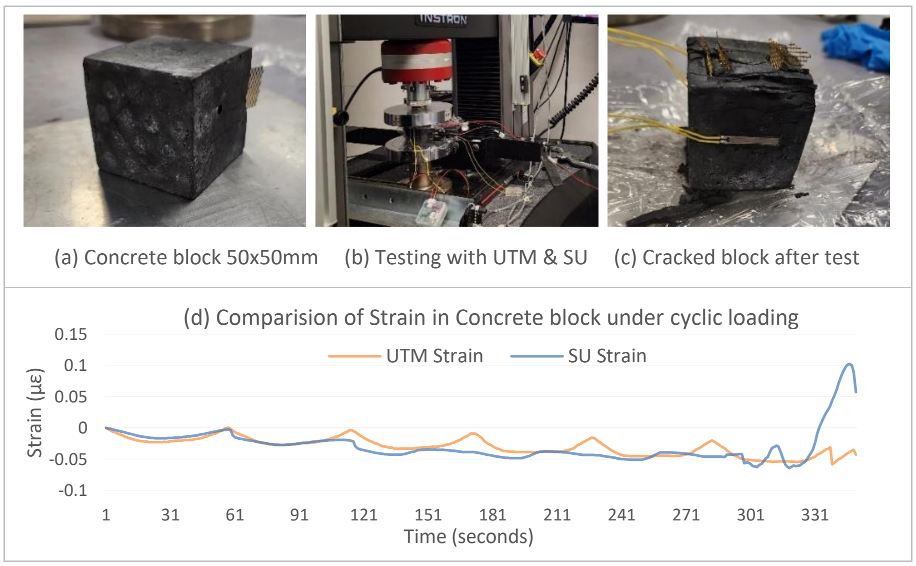


Figure 4-20. Strain test of the concrete block under cyclic load

4.3.5 IoT Sensing System Demonstration for MiC Logistics Damage Monitoring

A field experiment was conducted to demonstrate the effectiveness of the developed IoT sensing system. During the field experiment, the structure safety was monitored in real-time for any potential damage during MiC logistic operations. Besides any critical damage, the overall impact of logistics operations on the module's structure is also determined, which is helpful for proactive maintenance during the building use phase.

4.3.5.1 Experimental setup

The experimental setup was designed to emulate the real-world MiC logistic operations. The following sections explain the particulars of the subject module, the sensor installation process, and the observed logistic scenarios.

4.3.5.2 MiC Module

Considering the time and cost-effectiveness, a small wooden frame-based structure was built to be used as a module. The design of the wooden module was ensured to resemble the actual MiC module structure. The structural frame of this module was built using timber bars having a cross-section of 16x36 millimeters, ensuring reasonable structural strength for the module. The overall dimensions of this module were around 1600x500x500 millimeters, having a total weight of around 80 lbs., as shown in Figure 4-21(a,b). The module walls were built using thin balsa plywood with a thickness of 4mm, whereas the bottom base floor was 16 millimeters thick. Two timber base supports of 50x90 millimeters cross-section were also affixed at the bottom. The properties of the materials used are given in Table 4-2.

Table 4-2. Material properties of the built module

Materials	Elastic modulus	Density	Poison's Ratio
Timber Frame	14000 MPa	750 Kg/m3	0.18
Balsa Plywood Walls	4000 MPa	300 Kg/m3	0.35

4.3.5.3 SU installation

The eight SUs were installed on all corners of the module so SUs could sense the whole structure. This arrangement is considered for demonstration and experimental purposes in this study. In other cases, fewer SUs may be installed in selected critical and vulnerable positions on the module. Figure 4-21(c, d) highlights installed SUs' position as S1, S2, …, and S8. The SU's accelerometer will measure the vibrations in three directions, X, Y, and Z. Besides, the SU's gyroscope will measure the angular movements in three directions: roll, pitch, and yaw, as shown in Figure 4-21(e). For this study, the accelerometer and gyroscope were set to record measurements at 100Hz. However, the SU is programmed to transform the data streams into 1Hz by taking the mean of 100Hz data. This approach facilitates data syncing, real-time transmission, and managing the quantum of data while ensuring measurement accuracy [165].

Further, each SU can handle two strain gauge sensors installed on adjacent walls at each corner, as highlighted in Figure 4-21(c, d). The 15 cm long foil strain gauge sensors, having gauge factor 2, are installed at each wall corner. Such a long stain gauge sensor shall cover a larger corner wall area and sense the maximum strains in the walls. Besides, the strain gauge sensors are positioned at 45 degrees at each wall corner, as shown in Figure 4-21(c). The transportation and lifting operations of the module induce critical shear forces in the corners, causing cracks in walls [111]. Thus, installing strain sensors at 45 degrees will be capable of sensing the maximum possible strain. Hence, the installed strain gauges can sense any deformation anywhere in the structural element. The value of the measured strain will indicate the relative impact at the installed position of the strain and may not directly indicate the damage but the deformation. However, the relative strain impact of all the installed strains can be used to measure and locate the possible damage in the structural element.

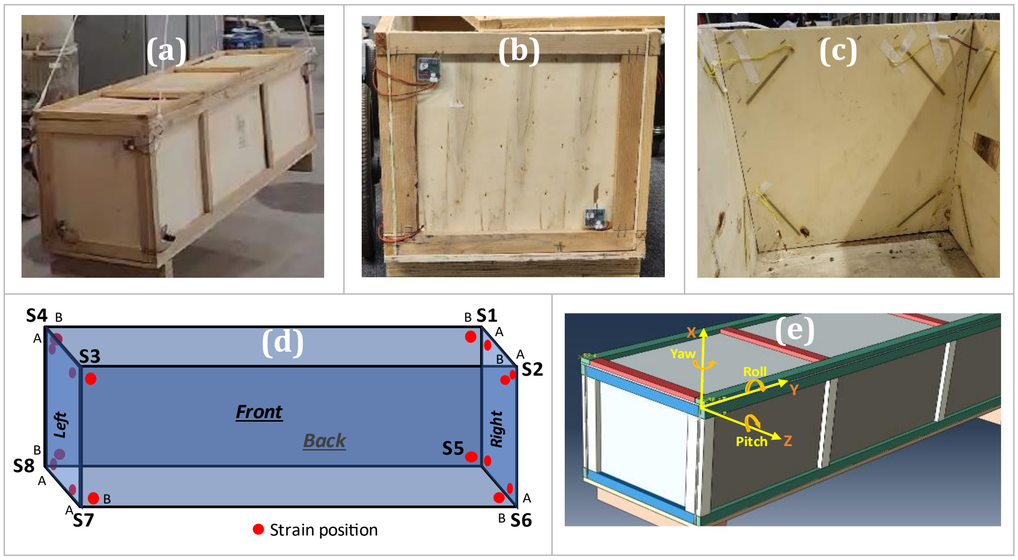


Figure 4-21. The SU and strain gauge installation on the built wooden module

4.3.5.4 Logistic Operations

The transportation and crane lifting processes were carried out to demonstrate the MiC logistic operations. For the first 600 seconds, a crane lifting operation was conducted. Hooks were installed on the four top corners of the module to tie the crane ropes. The module was lifted from the resting platform and hoisted around for a few minutes. The module was moved rigorously in all directions during the hoisting process that simulated the MiC assembly process. Then, the crane placed the module on a 4-wheel transportation trolly to simulate truck hauling. The module was transported around 200 meters away to the final destination. The transportation track involved a ruff tile-based track and a relatively smooth asphalt track. Also, it included several turns and inclined surfaces. The transportation speed varied at different points corresponding to the conditions, taking a total transportation time of around 800 seconds.

4.3.6 Damage Assessment Results and Discussion

During the field experiment, the IoT system provided a real-time response from all the sensors installed on the module. The real-time sensor response is plotted to analyze the events of logistic operations. The variations in the sensors' response help estimate the nature of the operation and any significant anomaly in that operation. The acceleration and gyro time series plots, shown in Figure 4-22, indicate various module movements during crane lifting and transportation operations. The crane lifting operation (between 0-600 seconds) was slow and smooth; thus, low acceleration variations were observed compared to transportation.

Similarly, the gyro response indicates restricted roll rotation as the module was tied on four corners during the lifting operation. On the other hand, the slight variations in yaw and pitch values during 150 to 300 seconds indicate the free movements of the hanging module. During transportation, the rough road section is highlighted by the high acceleration and gyro response in all directions from 770 to 1220 seconds.

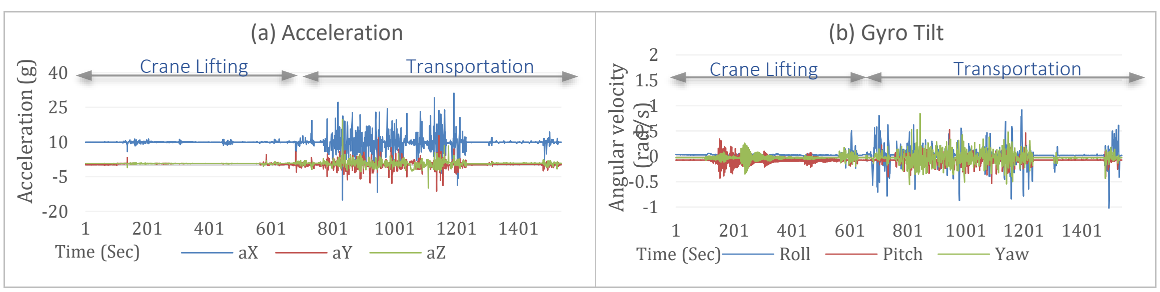


Figure 4-22. Time-Series of Acceleration and Gyroscope

The strain sensors' real-time response is shown in Figure 4-23. Despite the rigorous module movements in multiple directions, low strain variation is observed during the crane lifting. This was due to the low-hanging weight of the wooden module and the relatively smooth lifting operation. The sensors installed at the back and front module walls observed comparatively slight variation. However, these variations reach a maximum of 0.0045με, which is insignificant for a wooden module considering its material flexibility and cannot be confirmed as damage without detailed investigation.

Similarly, the strain values observed significant variation at the end of the crane operation as the module was placed on the transportation trolly. Such variation could be due to re-adjusting wooden parts according to the new support conditions, or it may indicate some damage. However, distinguishing such variations as damage requires additional analysis and investigation. Following that, during transportation, some of the sensors observed a slight drift that could indicate damage propagation under the vibrations induced by the rapid movement on the road.

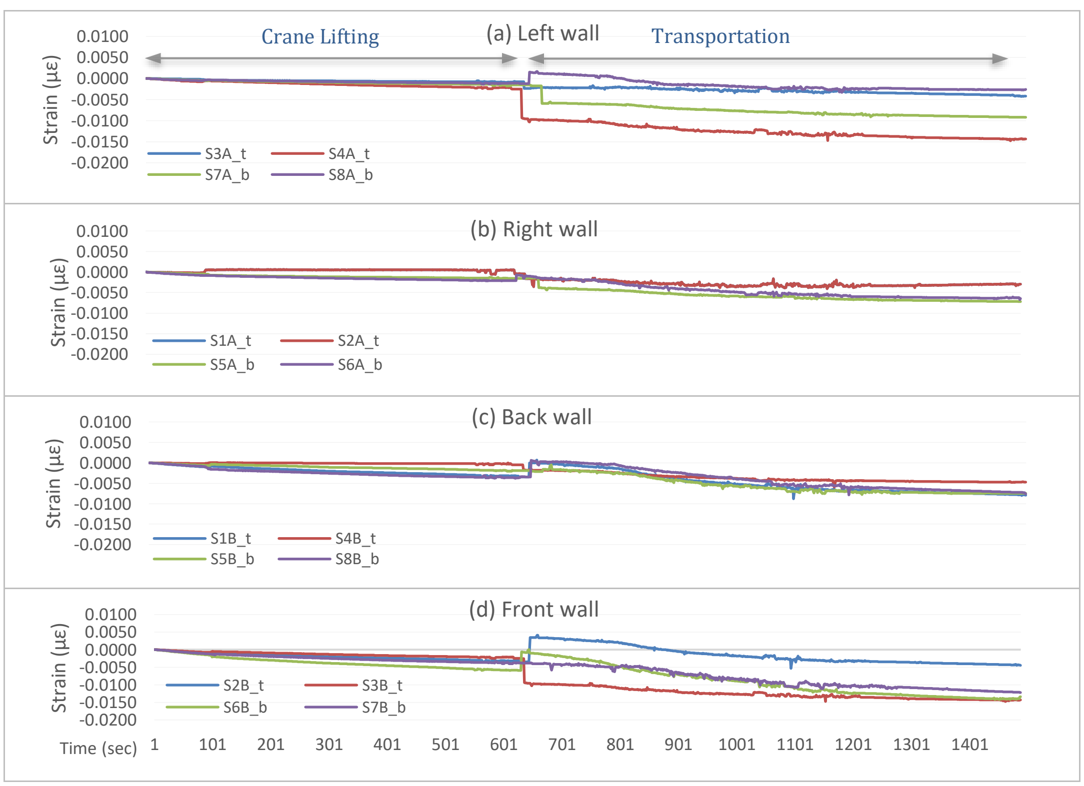


Figure 4-23. Time-Series of Strain Measurements

4.3.6.1 Real-time Damage and Safety Assessment

Several real-time exploratory analyses are performed to identify the potential damage and its location. These analyses can help the decision-makers investigate the sensors' response in detail and assess the possible damages while evaluating the relative response of sensors installed at various locations on the module. Further evaluation and comparison of all these analyses confirm the damage and its locations on the module.

Moving Average Window

The general sensors' response trends visualizations may not be helpful enough to predict damage in the module. Thus, the moving average window (MAW) is further analyzed to investigate the real-time sensor's response. This analysis represents the mean sensor response of a short period, called a window. This approach reduces the noise in the sensor response and represents actual changes that occurred in the structure [15,163]. A 30-second window is selected so that any point in the plot represents a structural change during that period. Such an approach is highly useful for real-time safety monitoring [76].

It can be seen in the moving average window plot, shown in Figure 4-24, that a significant strain change starts during transportation operations. For the right and back walls, the strain change remains less than -0.008 $\mu\varepsilon$ for all the sensors. On the other hand, the left and front walls experienced significant strain changes for most of the sensors attached. The sensors S2B_t show high strain displacement at the beginning of the transportation operation but later return to the average strain trend. The S7A_b shows moderate strain displacement reaching -0.01$\mu\varepsilon$. The sensors S7B_b, S4A_t, S3B_t, and S6B_b show the most critical response, where strain displacement keeps propagating and reaches up to 0.014 $\mu\varepsilon$.

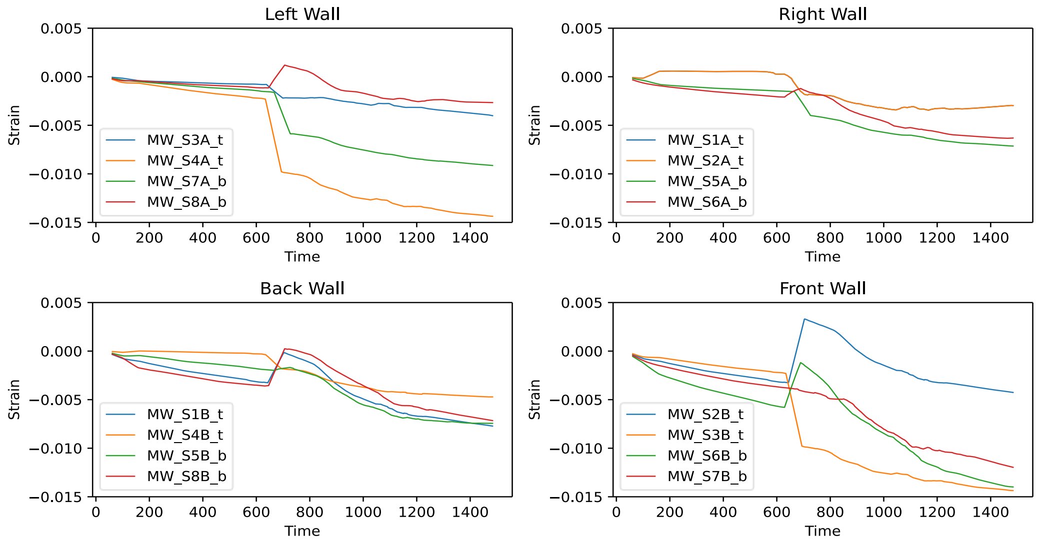


Figure 4-24. Moving Average Window Analysis

Expanding Average Window

Like the moving average window, the expanding average window (EAW) calculates the mean strain values. However, instead of using a window moving, all the previous data is considered to calculate the mean strain value for every new point. Such increasing window size optimally smoothens the window and helps estimate the accumulated variation in the sensor response [163]. Thus, the expanding average window analysis shows a net structural deformation occurring at any plot point.

The expanding window plot in Figure 4-25 highlights critical sensors similar to the moving average window. However, it shows more evident variations in the sensor response and indicates mean net structural deformations. The lines remain horizontal and closer to zero strain, indicating a net-zero deformation in the structure, and lines moving away from the zero signify structural deformations. The sensors installed on the right and back walls mostly show nearly horizontal closer to zero lines, thus revealing insignificant deformation in the adjacent walls. On the front wall, three sensors, S3B_t, S6B_b, and S7B_b, show a sharply deviating structural response indicating an evident deformation. Similarly, sensors S4A_t and S7A_b on the left wall show significant deformation.

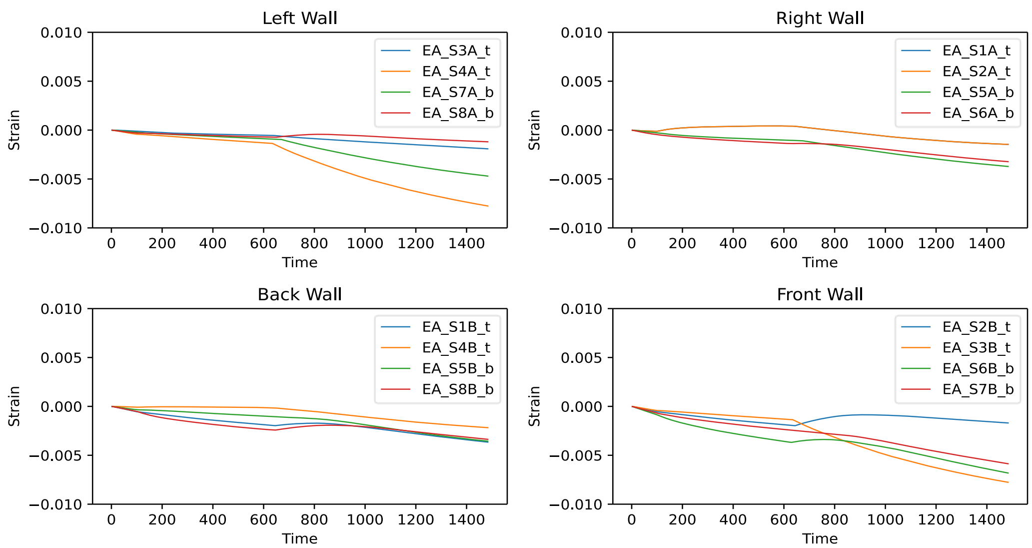


Figure 4-25. Expanding Window Analysis

Strain Field Histograms

The strain field histogram (SFH) helps to compare the frequencies of the discrete strain response values measured over time. Peak strain frequency indicates the amplitudes of various strain measurements, highlighting the variation in the measured response of several installed sensors [127]. Such variations may indicate the change in structural conditions near those sensors [15,16,307]. The SFH plots shown in Figure 4-26 suggest that the strains' range or spread is higher in the sensors installed on the left and front walls, reaching up to -0.0150 με. The sensors installed on the right and back walls measured the maximum strain displacement around -0.0075 με. The sensors S4A_t and S7A_b on the left wall and S3B_t and S7b_t on the front wall notably measured an abnormal response compared to other sensors. Also, unlike other sensors, the sensor S2B_t measured abnormal strain values up to 0.0025 με. The identified discrepancies in the sensor response led to estimating and locating the damages on the module walls.

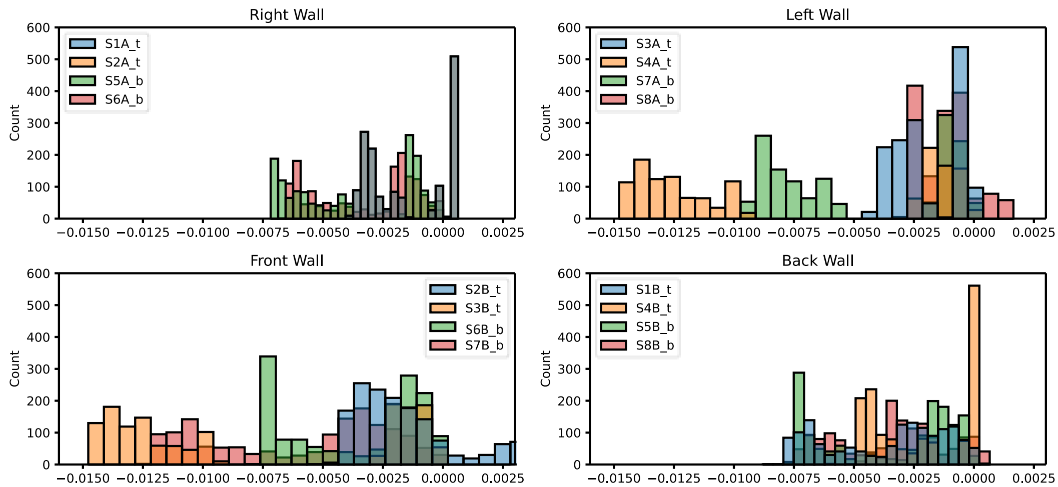


Figure 4-26. Histograms of Strain Measurements

Fast Fourier Transformation

A Fast Fourier Transformation (FFT) analysis is conducted to evaluate the acceleration and gyro sensors' response. The FFT magnitude provides the relative strength of various frequency components measured by each sensor. In the FFT spectrum, a distinguished higher magnitude frequency component called the dominant frequency represents the essential characteristics of the logistic operations [54]. In other words, the dominant frequencies indicate the primary structural response under the operations. Thus, if the dominant frequencies of sensors installed at various locations show any variation, it would suggest a change in the structural conditions at that point, i.e., structural damage [76,270].

Figure 4-27 shows the FFT spectrums of acceleration and gyro response observed for SU-S8. The FFT of each sensor shows multiple dominant frequencies (peaks) representing the non-stationary dynamic characteristics of MiC logistic operations. During all logistic operations, most module movements were along the vertical direction and the shorter side of the module, i.e., the x and z-axis, respectively. Thus, acceleration in the x and z-directions have more dominating frequencies. Meanwhile, the y-acceleration has only one distinguished high magnitude frequency (nearly 0Hz, called DC component), representing a dominant average structural response. The modules mostly remained tied along the y-axis and didn't experience any significant movements along this axis. For the same reasons, the roll rotation has fewer distinguished frequency components for gyro than the pitch and yaw rotations.

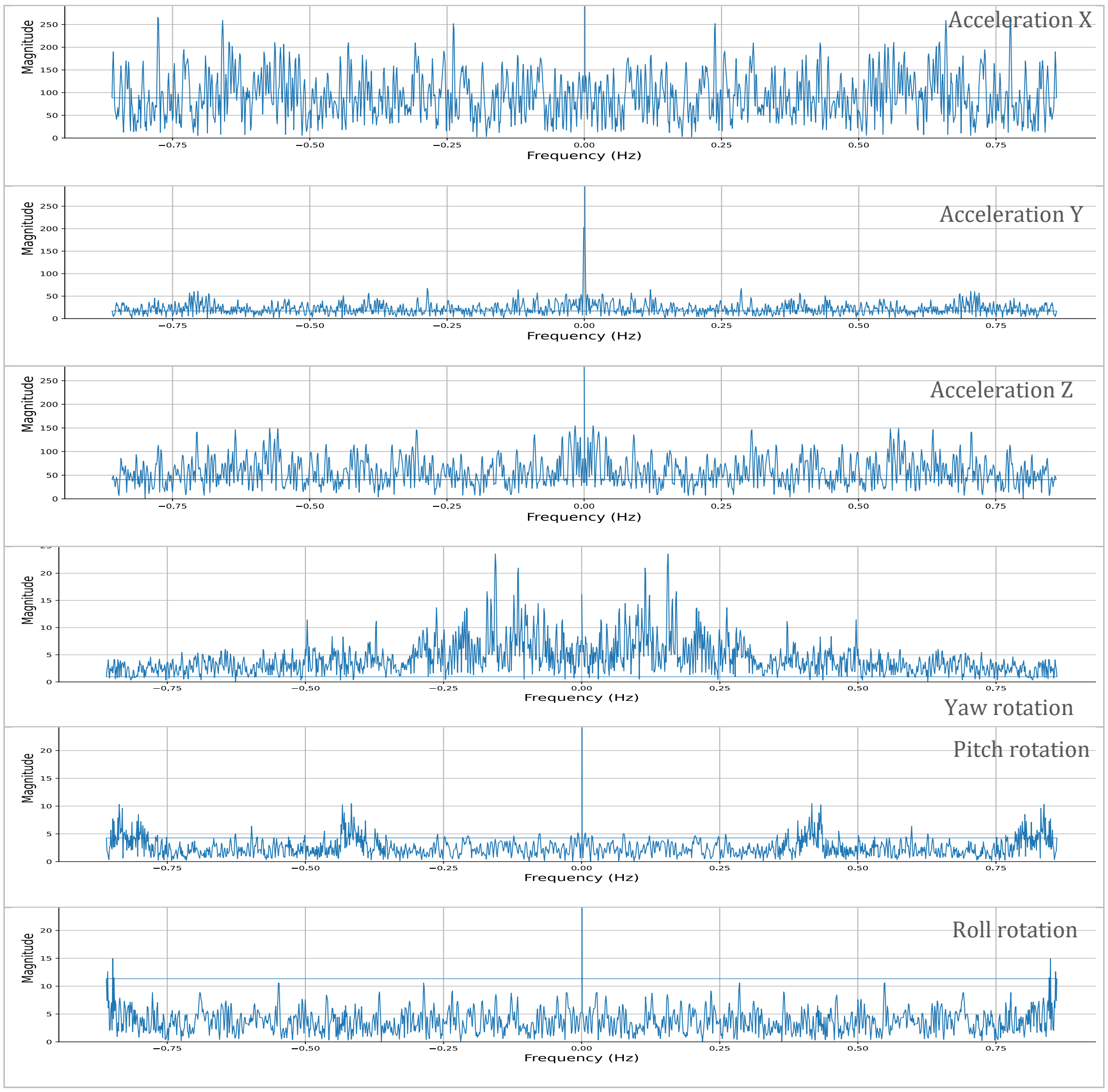


Figure 4-27. FFT of Acceleration and Gyroscope Measurements – S8

The FFT plots provide complex information, so comparing visualizations may not easily highlight or distinguish any variation. Therefore, all the installed sensors' interquartile ranges (IQR) are calculated to compare and evaluate the dominant frequencies. The values higher than the 3rd quartile can easily accommodate a signal's significant dominant frequencies. Similarly, the standard deviation (SD) of an FFT magnitude highlights the spread of the FFT magnitudes across the signal; any considerable variation in SD would indicate a change in structural response near that sensor. Thus, the SD and 3rd quartile can be critical indicators of the variation in the structural response [22,270]. Comparing these indicators of sensors installed at different locations can highlight the structural change. Table 4-3 presents the 3rd quartile and standard deviations (interquartile range) of all the acceleration and gyro sensors.

Along the x-axis, the acceleration and yaw rotations don't differ much across different sensors. Due to a complicated dynamic structural response in this direction, it has high noise and several distinguishing FFT magnitude peaks, leading to high SD and 3rd quartile values. Therefore, these sensors may not be suitable for detecting abnormalities. In contrast, along the y and z-axis, the acceleration and rotations have comparatively less noise and clear FFT magnitude peaks, thus revealing apparent differences across the sensors. The y-acceleration 3rd quartiles (61.47 a. units) and SD (27.80 a. units) of S1 are significantly higher than the other sensors. Similarly, the roll and pitch rotations of S7 and S8 showed minor differences.

To compare the discrepancies systematically and statistically at the location of different sensors, the normalized impacts of all the 3rd quartiles and SDs are combined by calculating net mean z-scores, as given in Table 4-3. The highest z-score of S6 (1.03) indicates that most variation has been sensed near this location, followed by S5 (0.97), S7 (0.90), and S8 (0.87). The 3rd quartile and SD values of acceleration and rotations for these sensors seem significantly abnormal compared to other sensors. Thus, damage is suspected closer to the location of these sensors.

Table 4-3. FFT Spectrum Interquartile Range

SU	X-accel		Y-accel		Z-accel		Yaw		Roll		Pitch		Net Z-scores
	std	3rd Q	std	3rd Q	std	3rd Q	std	3rd Q	std	3rd Q	std	3rd Q	
S1	380.89	133.82	27.80	61.47	32.30	46.68	3.22	5.54	3.25	3.23	2.06	4.60	0.83
S2	408.98	147.20	20.57	37.61	35.54	51.35	3.10	5.38	2.98	3.98	1.85	4.14	0.80
S3	383.45	123.39	17.06	39.90	35.38	87.06	3.33	5.60	3.15	4.78	1.89	3.01	0.61
S4	383.45	123.35	17.06	39.85	35.38	86.91	3.33	5.60	3.15	4.77	1.89	3.01	0.61
S5	376.62	142.55	14.02	33.62	23.22	46.66	3.30	5.44	3.25	5.05	4.76	3.30	0.97
S6	374.30	121.07	13.20	29.72	42.03	52.94	3.55	5.76	2.92	3.05	2.34	4.68	1.03
S7	381.55	120.93	15.08	32.02	22.77	53.75	3.34	5.44	2.07	5.07	1.54	3.17	0.90
S8	385.82	125.09	26.06	28.75	29.65	75.08	3.10	5.34	2.73	3.34	3.07	4.99	0.87

4.3.6.2 Damage Localization – Analyses Fusion

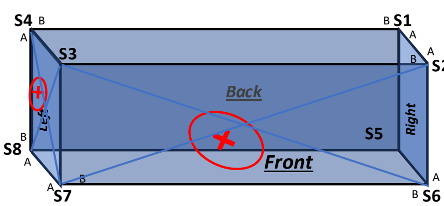
The analyses above highlight the potential damage in the structure while highlighting the critical sensors that sensed the most abnormal variations in the structural response. As a result, each identified critical sensor could have sensed the same damage from a distant location, or each analysis could have indicated different damage. Therefore, analyses fusion was performed to combine and compare all analysis results to confirm the damage and their respective locations. First, the critical sensors identified by each analysis are categorized into high, moderate, and low categories based on their variation criticality. Sensors in each category indicate that, for instance, the damage is either minor or away from the sensor location. Then, categorized sensors in each analysis are compared and combined as analyses fusion in Table 4-4.

The results highlight that the front and back walls experienced high and moderate levels of damage, respectively. On the front wall, the sensors S6, S6B_b, and S3B_t indicate high response variations, confirming critical damage on this wall closer to these sensors. The sensors S7 and S7B_b sensed moderated variations on the front wall, thus indicating damage location away from them. Similarly, the sensor S2B_t also sensed a low variation response on this wall, thus indicating the location of critical damage away from it. Considering the locations and relative impact sensed by these sensors, the approximate location of the damage can be estimated using a triangulation approach [67]. The high variations sensed by S6B_b and S3B_t imply the damage location in the middle of the diagonal between these two sensors. The moderate and low variation sensed by S7B_b and S2B_t suggests that the damage should be a little left and lower than the middle diagonal of S6B_b and S3B_t, as highlighted in the illustration in Table 4-4.

On the left wall, sensor S4A_t sensed a high response variation, indicating significant damage on this wall. Similarly, the sensors S7 and S7A_b, installed on the bottom right corner of this wall, also sensed moderate response variation. The S8 sensed low variations at the bottom left corner of this wall. Now, triangulating the relative impact sensed by each of these sensors, the approximate location of the damage is predicted, as illustrated in Table 4-4(a). The back and right walls didn't experience any significant damage. Only FFT analysis highlighted sensors S5 and S8 attached on the corners of the back and right walls. However, variations in these sensors are confirmed to be related to the front and left walls. The above-identified damage on the module walls can also be realized in the actual module, as shown in the pictures added in Table 4-4(b-d). Due to the wooden material of the module, they are hard to see visually. The damage and location predicted on the left wall are similar to the actual damage in the module. However, the predicted location of damage to the front wall is lower than the actual location. This assessment variation is possibly due to the module's loosely fixed top roof plane during the experiment, which interrupted the sensors' response installed at the top corners.

Table 4-4. Analyses Fusion for Locating Damages

Category	**MAW**	**EAW**	**SFH**	**FFT**	**Analyses Fusion**	**Impact Location**			
						Front	***Right***	***Back***	***Left***
High	S4A_t, S6B_b, S3B_t	S4A_t, S6B_b, S3B_t	S4A_t, S3B_t	S6	S4A_t, S6B_b, S3B_t, S6	✓✓✓	✓		✓
Moderate	S7B_b, S7A_b	S7A_b, S7B_b	S6B_b, S7A_b, S7B_b	S5, S7	S7B_b, S7A_b, S5, S7	✓✓	✓	✓	✓✓
Low	S2B_t	-	S2B_t	S8	S2B_t, S8	✓		✓	✓



(a) Predicted Damage Locations


(b) Left wall


(c) Right wall

4.3.6.3 Module's Health Impact Assessment

Besides any critical crack or damage in the module structure, some hidden, intrinsic underlying, minor latent damages could remain undetectable. Such minor damages are induced in the structure due to rigorous MiC logistic operations and can further propagate into critical damages during the building use phase. Therefore, it is essential to assess the overall impact of logistic operations on the health of the module structure. Such an assessment can help devise a proactive maintenance schedule for the module and improve the module's useful life.

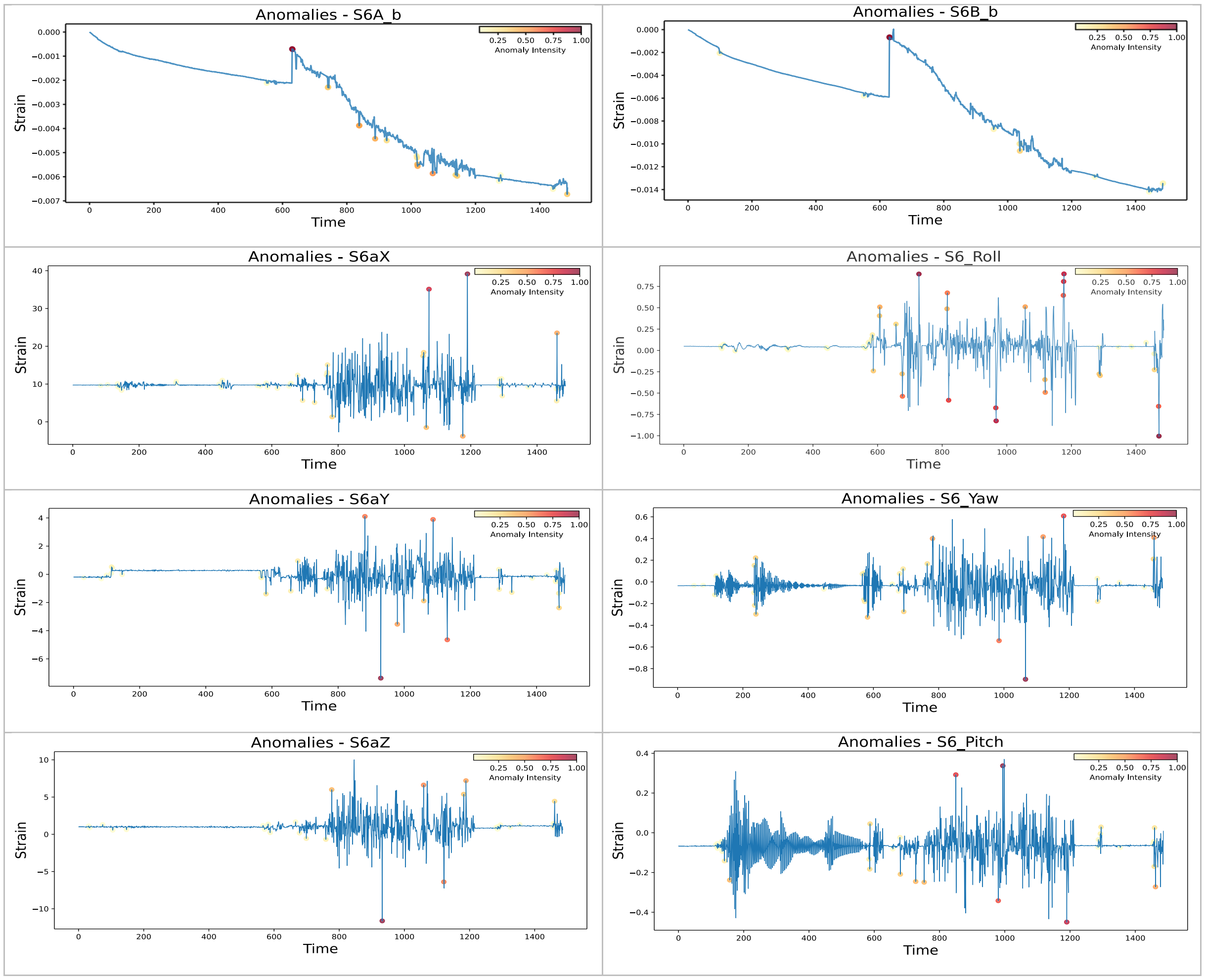


Figure 4-28. Detected anomalies (as red dots) by sensor S6.

The adopted approach exploits the typical anomaly detection approach, as all the abnormal logistic impacts are accumulated to calculate the relative impact over different module parts. For anomaly detection, any sensor response in a moving window exceeding the defined threshold is identified as an anomaly [76,325]. Considering a 30-second moving window and one SD (standard deviation) as a threshold, all the anomalies sensed by each sensor were detected. A programmed model detected all the anomalies in real-time during the logistic operations, as shown in Figure 4-28. The weight of each anomaly during logistic operation is assessed and categorized as high, moderate, and low according to their relative weights. Anomalies are systematically aggregated to calculate a total weighted sum of anomalies for each category at each module wall.

Table 4-5 compares the high, moderate, and low impacts experienced by each type of sensor for all the module walls. The strain sensor results coincide with the real-time safety assessment in the previous section. It indicates the significant impacts on the front and left walls, 22.90% and 10.89%, respectively. However, the accelerometer suggests different patterns of impact on the module walls. It indicates the highest impact on the right wall (17.52%) and no impact on the left. The impacts on the front and back walls also vary from the strain sensor assessment. Such variation could be due to the high precision of the strain sensor for assessing closer impacts in contrast to the accelerometer, which can also assess the response from farther locations. Thus, the strain gauge should be considered more relevant for evaluating significant local damage, such as cracks or deformations. However, the acceleration-based assessment could be more useful when assessing the overall structural changes during the stationary building use phase.

Table 4-5. Overall Module's Health Impact Based on Sensor Fusion Scenarios

Impact Level	**Right Wall**	**Back Wall**	**Left Wall**	**Front Wall**
		Strain Only Impacts		
High	9.35%	0.00%	13.55%	**22.90%**
Moderate	1.25%	**10.89%**	9.64%	0.00%
Low	1.56%	0.03%	0.00%	1.53%
Total Impact	12.15%	10.92%	**23.19%**	**24.42%**
		Acceleration Only Impacts		
High	**17.52%**	8.91%	0.00%	8.61%
Moderate	8.65%	5.08%	0.00%	3.57%
Low	0.00%	1.81%	2.31%	0.50%
Total Impact	**26.17%**	15.81%	2.31%	12.67%
		Gyro Only Impacts		
High	**5.14%**	1.81%	0.00%	3.33%
Moderate	0.00%	1.06%	2.95%	1.90%
Low	0.67%	0.00%	1.40%	2.07%
Total Impact	**5.82%**	2.87%	4.35%	**7.30%**

Sensor Fusion

Each type of sensor has varying sensitivity to different kinds of motion during logistic operations. An accelerometer, measuring linear acceleration impacts, has significant sensitivity to linear motion, such as transportation. Therefore, the acceleration-based anomalies would be considerable for interpreting the damage induced by any transportation motion. Similarly, the gyroscope, measuring the rotational velocity impacts, is mainly appropriate for interpreting the lifting, loading, and unloading operations. On the other hand, the strain gauge, measuring the direct structural variations, should be relevant to interpret impacts from all logistic operations. The previous section also observed such assessment patterns for strain, accelerometer, and gyro sensors.

Therefore, we propose the weighted average-based sensor fusion to determine the overall impact on the module. The sensor fusion-based impact (I_{fusion}) can be calculated using Equation 4-2, where S, A and G represents the measured impacts and w_s, w_a and w_g represents the corrosponding weights. The decision maker can select the appropriate weights according to the type of logistic operations. For example, if logistic operations involve only transportation, the strain and accelerometer impacts can be considered with (0.5) weights each, neglecting the gyro impact. On the other hand, if logistic operations are mainly lifting or loading and unloading, the strain and gyro impacts can be considered, ignoring the accelerometer.

$$I_{fusion} = S.w_s + A.w_a + G.w_g \qquad \text{Equation 4-2}$$

As our field experiment involved both crane lifting and transportation logistic operations, we selected equal weights (0.33) for all the sensors and calculated the fusion-based impacts. Table 4-6 shows the sensor fusion results. Overall, the front and right walls experienced the most impact, 8.79%, and 8.70%, respectively. Significantly, the right wall didn't experience any critical damage, as assessed in the previous section. However, the anomalies assessed on this wall highlighted the possible effect on the overall health of this wall compared to the left wall.

Table 4-6. Sensor fusion-based module health assessment

Impact Level	Right Wall	Back Wall	Left Wall	Front Wall
High	**7.09%**	0.00%	0.94%	**8.04%**
Moderate	1.48%	3.85%	2.38%	0.00%
Low	0.13%	0.00%	0.62%	0.75%
Total Impact	**8.70%**	3.85%	3.94%	**8.79%**

4.3.7 Summary (Objective III)

The study embraces the real-time monitoring of the module’s structure during MiC logistic operations. A smart, integrated, portable, IoT-based sensing system is designed to ensure its practicality for MiC logistics. A smaller form factor of sensing units is achieved to keep it practically invisible while installed on a module. The developed sensing system was calibrated by incorporating temperature compensation factors and turn-on bias elimination. The sensing system performance is thoroughly tested in different conditions, and accuracy is found to be comparable to that of standard commercial equipment like UTM.

The module's real-time structural condition monitoring enables early damage detection, allowing timely decisions to avoid supply chain disruptions. Also, it can improve the on-site safety inspection process while providing more insights into the module’s structural condition, increasing inspection speed, and highlighting the latent damages. Moreover, the safety of the real-time assembly process can be monitored. The sensing system provides detailed structural response data of logistic operations, which is useful for predicting the module's structural creep and forecasting maintenance during the building use phase. Thus, the system helps to ensure the JIT supply chain for MiC assembly, enhances assembly process safety, and helps to improve the module's service life.

The application of the developed sensing system is demonstrated with a field experiment, and various analyses are presented to detect critical damage and assess the overall impact on the module's health. The demonstrated field experiment not only evaluated the system's effectiveness but also highlighted the effectiveness of different sensors in assessing the structural condition. The strain sensors are found to be more sensitive toward structural deformation and are directly helpful for determining the critical damage and its location. On the other hand, acceleration data is less sensitive but more helpful for assessing global structural deformations and overall structural health assessment. The gyroscope sensor's accuracy in predicting damage advocates its relevance but shows a complex relationship requiring deeper and more complicated analyses. Such insight can help understand the optimum number of sensing units required during the logistics and building use phases and the most suitable location for installing sensors. However, further elaboration needs future research with this perspective in particular. Such future elaboration can also help improve the device and its performance. Moreover, the developed system is demonstrated using a wooden module for cost-effectiveness. However, further validation is needed for steel and concrete types of modules.

The developed sensing system employs state-of-the-art micro technologies, which can embed Artificial intelligence (AI) algorithms on the device. This feature allows for instantly sensing, assessing, and predicting the structure condition on the device, reducing the raw sensor data transmission and processing requirement and, hence, improving portability. The sensing system opens new research avenues for researchers by accessing detailed information on structural response during logistic operations. It will help to understand the structural dynamics under various scenarios of module handling during logistic operations. It will help improve the structural design and the module logistics strategies to save cost and time. Also, in the future, the sensing device can be further developed to facilitate the automation of the assembling process.

4.4 A Hybrid Deep Learning Model for Damage Assessment in MiC Modules

(Objective IV)

4.4.1 Introduction

This study opts to develop an integrated CNN-GRU deep-learning model for MiC damage assessment of MiC module during logistic operations. The proposed deep learning model incorporates multi-sensor time series data, effectively incorporating the spatial correlations among the loading impacts, corresponding structural responses, and variation along the time sequences. The following section discusses the developed architecture and the model implementation.

4.4.2 CNN-GRU Combined Model Architecture

There are two main approaches to combining the CNN and GRU models: parallel and hierarchical. Both approaches have benefits and limitations, and selection depends on the data type, model objectives, and preferences. Some studies adopted the parallel approach, in which sensor data is simultaneously passed to CNN and GRU, and both outputs are combined [47,345,367,378]. In the hierarchical approach, first, the CNN model extracts the features and learns the correlations and patterns among multiple sensor signals within a given time sequence. Then, CNN output is reshaped and passed to the GRU model, which learns the long-term dependencies among the time sequences [346,371]. However, parallel architectures equally focus on both dimensions, and they are more complex, computationally expensive, and less efficient for large data sets [266]. In this context, the hierarchical approach is more desirable when the input data contains a dynamic hierarchy and the objective is to explore across hierarchies in all dimensions [38,49]. Thus, this study adopts a hierarchical combination approach for combining CNN and GRU.

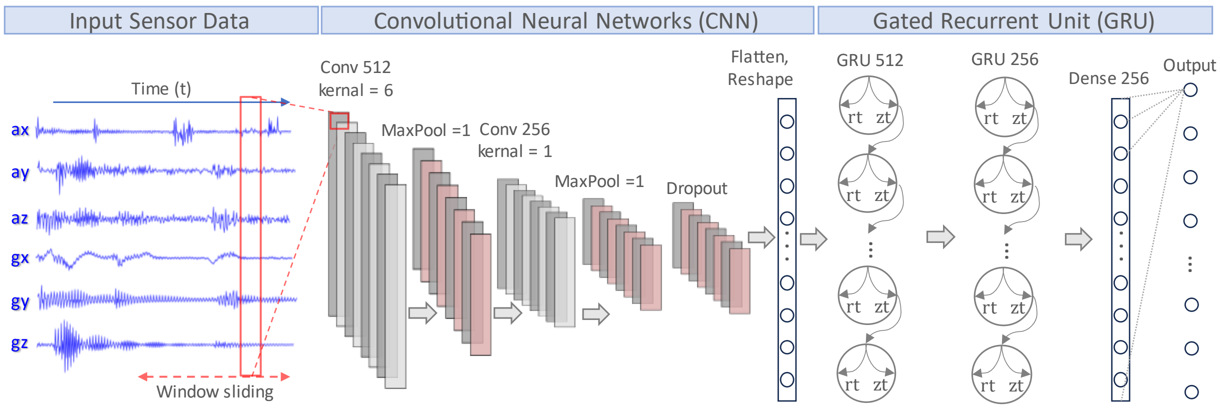


Figure 4-29. Proposed CNN-GRU architecture for structural strain prediction regression model.

The developed architecture is a sequential neural network where layers are stacked sequentially, as shown in Figure 4-29. It combines CNN and GRU for feature extraction and sequence modeling. The shaped sequences and corresponding features (6 sensor signals) are passed to the first CNN convolutional layer. This layer learns to recognize local patterns in the input sequences, resulting in a feature map as output (z_i). The Equation 4-3 below represents the operation of the convolutional layer. Where, z_i represents the output at position i, x_{i+j} denotes the input signal value, and w_j represents the weight of the filters, and b is the bias term.

$$z_i = \sum_{j=0}^{5} x_{i+j} . w_j + b \qquad \text{Equation 4-3}$$

The convolutional layer is set to have 512 filters that slide over each input sequence to extract specific patterns. A higher number of filters allows more diverse feature learning but increases model complexity. The kernel size in this layer is set as $F = 6$, meaning filters will slide over all six input features in each sequence. Larger kernel sizes capture broader features, while smaller sizes focus on finer details. A LeakyReLU activation function is adopted to prevent the vanishing gradient by considering a small negative slope (0.01). The resulting feature map from the convolutional layer is passed to the max-pooling layer. This layer is an essential part of CNN to reduce the spatial dimensions of the feature map and computational expense. This model sets the pool size as one, as no reduction was required.

Another batch of convolutional and max-pool layers was added to enhance the model complexity and deepen the learning. This time, the convolutional layer was set to have 256 filters, with kernel size $F = 1$. Due to a smaller kernel size, this layer refines spatial features and trains more fine details. Following this, a dropout layer (rate 0.01) is added to prevent overfitting during training by randomly deactivating a fraction of neurons. Then, the resulting feature map output is transformed to match the required shape with the next layer. For this purpose, first, a flattening layer is added that converts the two-dimensional feature map into a one-dimensional vector, followed by a reshaping layer to get the required shape.

The reshaped feature map extracted by CNN layers is then passed to the GRU layer for sequence modeling. The GRU then extracts the features to learn the long-term dependencies among the input sequences. Similar to the CNN, two GRU layers are added for robust training. The first GRU layer has 512, and the second layer has 256 filters with a LeakyReLU activation. Equations 4-4 to 4-6 explain how the GRU processes the input data and generates the output. Where, x_t is the input matrix, z_t, r_t and h_t denote update gate, reset gate, and hidden state, and w_z, w_r and w_h are their respective weights. The σ

and $tanh$ are sigmoid and hyperbolic tangent activation functions that calculate and make decisions for z_t and r_t.

$$z_t = \sigma(w_z.[h_{t-1}, x_t] + b_z) \qquad \text{Equation 4-4}$$

$$r_t = \sigma(w_r.[h_{t-1}, x_t] + b_r) \qquad \text{Equation 4-5}$$

$$h_t = (1 - z_t).h_{t-1} + z_t.(tanh(w_h.[r_t.h_{t-1}, x_t] + b_h))) \qquad \text{Equation 4-6}$$

GRU maintains a hidden state that keeps updating with new inputs. The update gate (z_t) and reset gate (r_t) control how much information from the previous hidden state should be retained and how much to forget. The hidden state (h_t) combines the previous hidden state and the new information, controlled by the update gate. So that, if $z_t$is near zero, most new information is updated in the h_t, or if it's closer to one, information from the previous state is retained. The output of a GRU layer is the last hidden state at each time step. This GRU output is passed to the dense, fully connected layers. Dense layers learn the complex mappings from the previous layer's features and apply a linear transformation followed by a nonlinear LeakyReLU activation function. The proposed architecture contains a dense layer with 512 filters, followed by a single filter layer that converges to the output layer.

4.4.3 Experimental Results and Analysis

4.4.3.1 Experimental Setup

A field experiment was conducted to collect the sensor data related to MiC logistic operations. A MiC module was designed with dimensions 1.6 × 0.5 × 0.4 meters, weighing around 35 kg. The design followed a frame structure to ensure structural resemblance with the actual MiC module structure, as shown in Figure 4-30(a). However, the module frame was built using timber wood, while the walls, floor, and roof were made of balsa plywood.

The experimental cost and convenience rationalized the choice of material for this experiment, as the purpose is to demonstrate the developed deep learning model and damage assessment frameworks.

The experiment was conducted in two phases. A healthy (undamaged) module recorded deep learning model training data in the first stage. In the second stage, a damaged module was used to collect data to compare and evaluate damage. The transportation and crane lifting processes were performed during this experiment, imitating the actual MiC logistic operations. For the training and test data, logistic operations were carried out for 25 minutes, and the structural response from the module was recorded. For the first 10 minutes, a crane lifting operation was performed. The data for several module hoisting, lifting, placing, hanging, and swaying steps were captured during this operation.

Following the crane lifting, the transportation process continued for 15 minutes. The module was placed on a truck and hauled at different speeds on smooth and rough road tracks. Sharp turns and accidental breaking scenarios were also included to capture representative data for MiC road transportation. The total duration for the second phase of the field experiment was 10 minutes, consisting of five minutes of crane lifting and five minutes of transportation operation.

4.4.3.2 Data Acquisition System:

A multi-sensing IoT-based system was developed to sense the structural response of the module during logistic operations. This system consists of two devices: (a) a sensing unit and (b) a communication unit, as shown in Figure 4-30(c, d). The sensing unit (SU) is a portable, compact device that integrates multiple sensors: an accelerometer, a gyroscope, and a strain sensor analog-to-digital converter (ADC). The in-built microcontroller and wireless communication modules enable this device to control the sensed information from the sensor and wirelessly transmit it. Several SUs installed on a module transmit real-time sensor data to the communication unit (CU). The CU is a power communication and data management device that receives data from all the installed SUs, processes and organizes the sensor data, saves data in the in-built memory, and transmits it to the internet-based server. Further details of the development of the IoT sensing system and its features and performance are provided in [26].

For the experiment, a total of eight SUs were installed at each module corner, as shown in Figure 4-30(b). The 15cm long foil strain gauges were installed on the inner wall surfaces at a 45-degree angle to measure the maximum shear strain in the wall. Each SU can connect two strain gauges, connecting a total of sixteen strain gauges fixed at each wall corner. Such an arrangement effectively measures the structural response from the whole module structure. The accelerometer in the SU measures up to ±16 g acceleration in the 3-axis (x, y, and z), and the gyroscope measures the roll, pitch, and yaw angles at ±2000 dps angular/rotational speed. The SU was set to measure the sensors' reading at 100 Hz. However, the high-frequency sensor data was transformed into mean amplitude at 1 Hz while maintaining the data accuracy. Such a reduction in data quantum is essential to effectively manage the high quantum of data transmission, storage, and syncing [165].

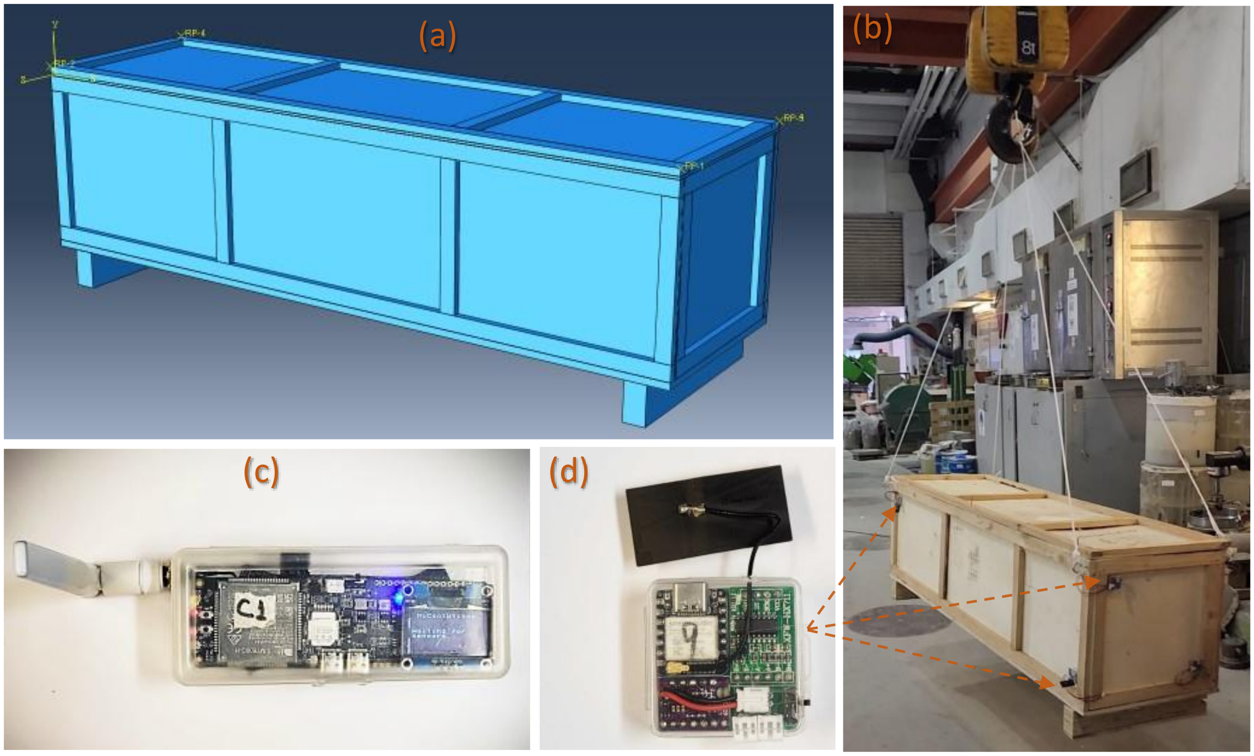


Figure 4-30. Experimental setup: (a) the designed wooden module, (b) the module during logistic operations, (c) the communication unit (CU), (d) the sensing unit (SU).

4.4.3.3 Deep Learning Model Training and Testing

The data acquired from the field experiment contained sixteen combinations of sensor data from all locations on the module. All these data sets were combined by stacking over each other to obtain a large data set for model development. The sensor data is a time series where sequential dependencies are important. Therefore, traditional data splitting for training and testing is not suitable in this case. Instead, sensor data collected from one location was reserved for testing. Following the data preprocessing, as explained in the model architecture, the model was trained. The Adam optimizer and the mean absolute error (MAE) loss function were used for compilation.

The training is controlled by a learning schedule and early stoppage callback functions to avoid overfitting. The dynamic learning schedule allowed the 0.001 for the first five epochs and, after that, reduced the learning rate (LR) based on the Equation 4-7**.** Where the initial rate (Ir) is 0.001, the drop rate (r_{drop}) is 0.5, and epochs drop (e_{drop}) is 10.

$$LR = Ir * (r_{drop} * (1 + epochs)/e_{drop}) \qquad \text{Equation 4-7}$$

The patience for the early stop function was set as three so that model training automatically stopped when there was no improvement in the loss for three consecutive epochs. The model training was completed after 83 epochs, as shown in Figure 4-31**.** The model training had a training loss of 0.011 and a validation loss of 0.000146. Here, the gap between the training validation loss is due to the use of dropout regularization layers in the training, which deactivates the weak neurons. Such regulation shows a difference in training losses but significantly improves the model resilience.

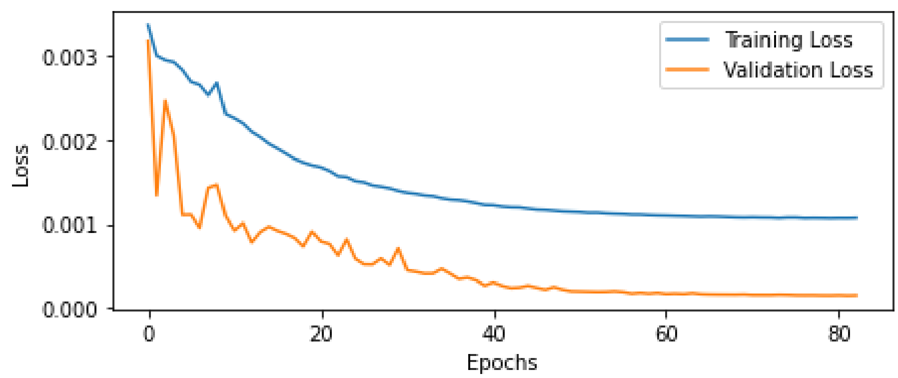


Figure 4-31. Deep learning model training loss-epochs plot

Test data Predictions

Further, test data predictions are generated from the model to evaluate the accuracy. The comparison of the actual and the predicted strain values is plotted in Figure 4-32(a). It can be seen that the strain values are predicted accurately, as the trend of the predicted values exactly follows the actual values, with only a few exceptions. Similarly, the residual plot in Figure 4-32(b) also highlights the model accuracy, as most residuals remain along the center line, having a 2.5x10^{-5} mean value.

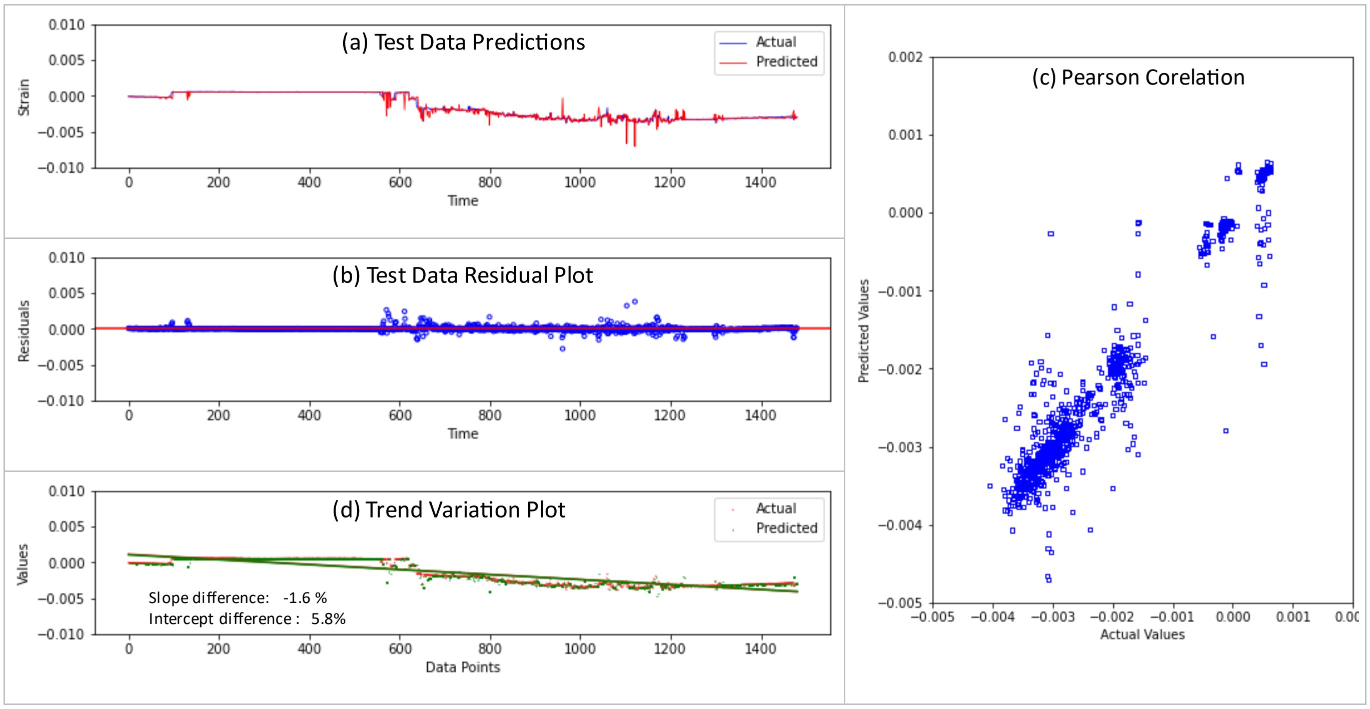


Figure 4-32. Test data predictions

Model performance evaluation metrics

The performance of standalone CNN and GRU models is compared with the developed hybrid CNN-GRU model for evaluation. For comparison, the model parameters are kept consistent for these standalone and hybrid models. Several performance statistical metrics are determined and compared to evaluate the model's accuracy. The coefficient of determination (R^2), mean absolute error (MSE), root mean square error (RMSE), mean square error (MAE), standard deviation of residuals (SDR), and Pearson correlation coefficient are widely used metrics for the evaluation of a regression model. The hybrid CNN-GRU model outperformed the standalone CNN and GRU models across all performance metrics, as shown in Table 4-7.

The coefficient of determination (R^2) explains the level of relationship between the prediction and input features, indicating the variance proportion. R^2 score 0 means that the predictions do not relate to the input features, whereas R^2 score 1 means the predictions are 100% representative of the inputs. The R^2 score of the test result predictions from the CNN model is 0.6, indicating that the CNN model results could partially relate to the input features. The GRU model encompassed a substantial (0.88 R^2) relation among predictions and features. Meanwhile, the developed hybrid model showed 0.9625 R2, highlighting that the model is performing well and that the predictions from the developed model highly relate to the input features.

Table 4-7. Deep learning model performance metrics

Metrics	R^2	MSE	RMSE	MAE	SDR	PCC
CNN-GRU	0.9625	1.074×10^{-7}	0.000328	0.000146	0.000327	0.98
GRU	0.8824	3.384×10^{-7}	0.000582	0.000322	0.000581	0.94
CNN	0.6003	1.144×10^{-6}	0.001069	0.000530	0.001059	0.84

The mean square error (MSE) is also a reliable metric of model performance that quantifies the average squared difference between predicted and actual values, measuring the model's prediction quality. MSE for the developed deep learning model has a very low value ($1.074\text{x} \ 10^{-7}$) compared to CNN and GRU models. Such a low MSE suggests the model's predictions are very close to the actual values. RMSE is the root of MSE that provides an interpretable measure of the average error in the units of the target variable. Compared with the actual test data range (max: 0.000634, min: -0.004051), a 0.000328 RMSE indicates only a 0.93% prediction error. Like RMSE, MAE is also more unadorned to interpret since it's in the same units of the target variable. MAE represents the average magnitude of prediction errors, calculated as the average absolute difference between predicted and actual values. A small MAE value of 0.000146 indicates only a 0.89% error in the predictions, highlighting negligible absolute differences between predicted and actual values.

Standard Deviation of Residuals SDR measures the variability or dispersion of the residuals. A higher SDR indicates that the model's predictions have more variability around the actual values, whereas a lower SDR suggests that the model's predictions are more consistent. The SDR value of 0.000327 is too small compared to the standard deviation of test data (0.001692), suggesting that the residuals are close to the regression line, indicating a good model fit. Another model performance metric, the Pearson correlation coefficient, measures the linear relationship between predicted and actual values. A high correlation coefficient (0.98) indicates a strong linear relationship, reflecting the model's ability to capture the underlying patterns in the data. The plot of Pearson correlation between actual and predicted, shown in Figure 4-32(c), also indicates a linear relationship, as 98% of data points are clustered around the centre diagonal line.

4.4.4 MiC Module Damage Assessment

Another field experiment was performed with a damaged module to validate the developed model with unseen data and demonstrate the damage assessment method. During the logistic operations, two different damages were introduced in the module structure at two different times. The first damage was introduced during the crane lifting at the top corner of the left and back wall at the 96th second of the logistic operations. Such damage was opted to simulate a joint failure and was activated by removing a nail from that corner of the structure. The second damage was introduced during the transportation operation by introducing a critical crack in the front wall at the 430th second of the logistic operations. The damage locations on the modules are illustrated in the Figure 4-33.

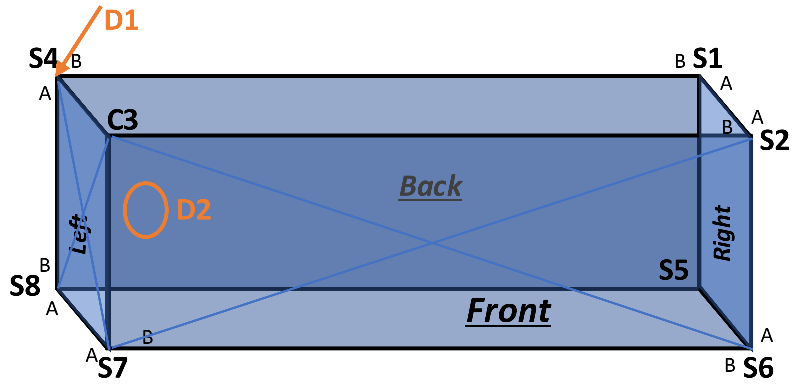


Figure 4-33. Location of damages on the module

The developed deep learning model then predicted the strain values for the logistic operations. The model predicts the expected strains for those logistic operations for an undamaged module. If the actual measured strain values show significant variation from the predicted values, indicate damage. The comparison of the predicted strain values with the actual measured strain values for each sensor location is plotted in Figure 4-34**.** It can be seen that the predicted and actual strain values of S4 on the left wall start showing maximum variation after the time 96 seconds when the damage was introduced. The S8 on the bottom left wall showed no significant variation after the damage occurred until the module was placed on the ground after completing the crane operation at around 300 seconds. The S8 location is away, so there were no immediate variations. However, the damage occurrence changed its constraint conditions, and damage was revealed after the state of loads was altered significantly after placing it on the ground.

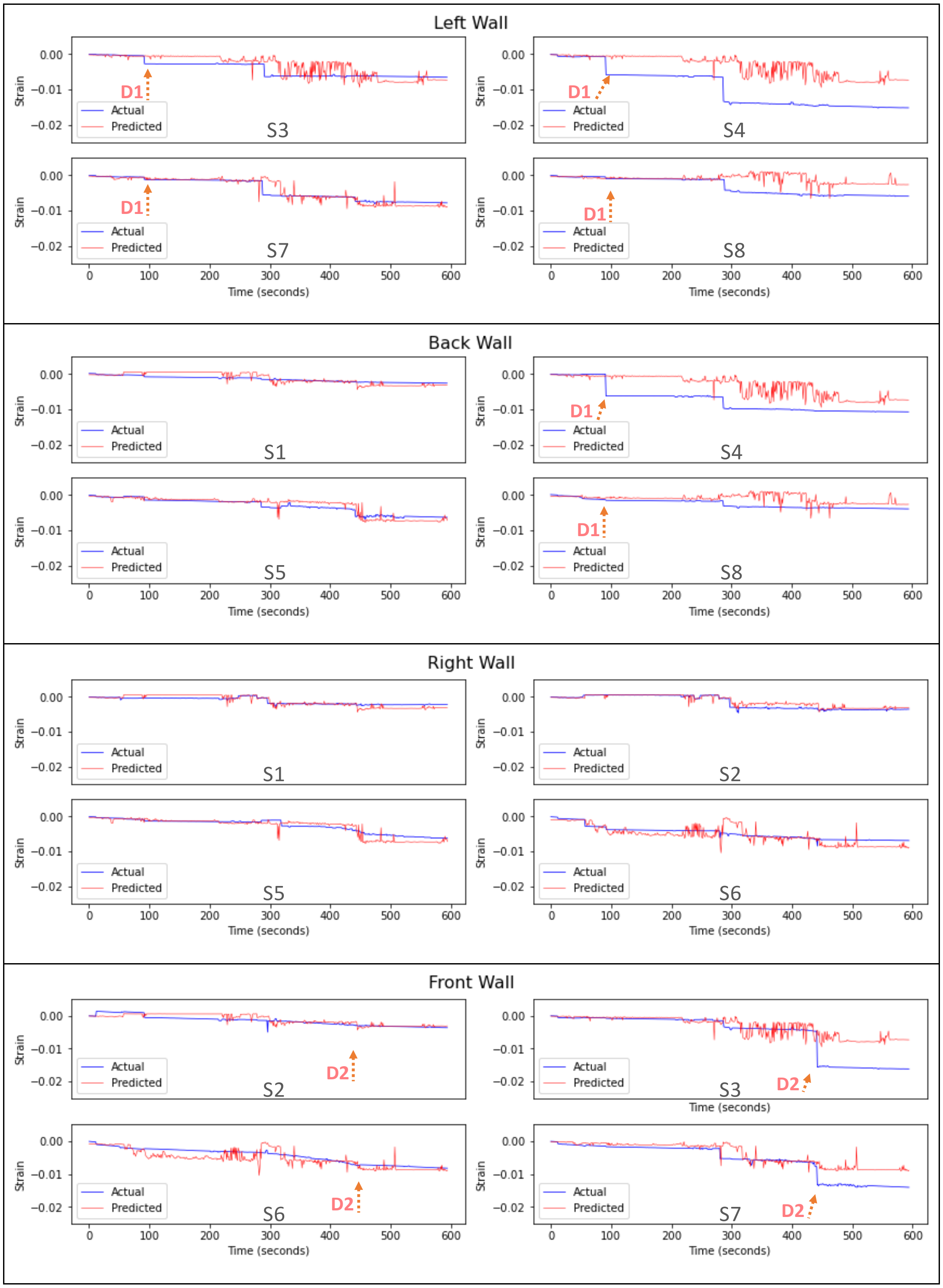


Figure 4-34. Plot of measured strain values with predicted strain values

Similarly, the S3 shows marginal variation at the time of damage and after putting it on the ground. The S7, away from the damaged location, shows almost no variation. A similar pattern can be seen on the back wall, where the actual measured strain values of S4 show significant variation after the first damage, and S8 revealed variation at the end of the crane operation. The S5 and S1 on the back wall showed negligible variations, as they are away from the location of the first damage. The right wall had no damage nearby; thus, all the installed senor locations showed measured strain following the predicted strain value.

The second damage was introduced in the front wall closer to the S3 and S7 locations. Therefore, it can be seen in Figure 4-34 that the strain values measured at the sensor locations S2 and S6 tend to follow the predicted strains, showing no significant damage. In contrast, S3 and S7 start showing substantial variation after 430 seconds when the second damage occurred. Notably, the measured strain values of S2 and S6 generally follow the trend of the predicted strain values. However, a minor mismatch in individual instances is visible in the plots.

Such behavior is also visible at other locations due to the natural heterogenetic properties of wood. Heterogeneity is due to the wood's varying density and moisture content at different times, causing varying strain responses. Wood is also a complex cellular structure-based material, where some fibers may show different strain responses at different times, causing irregular variations. Despite such limitation of wood material, the damage assessment is based on the overall strain trend, reflecting the overall structural strengths.

As for the evaluation of structural damage assessment, the strain sequence trend is more important than the variation at individual time instances. The predicted strains and measured strain trend lines are compared in Figure 4-35**,** where a higher slope and intercept difference indicates a higher level of damage. For the left wall, the difference between the trend lines for S4 is too high, while S3 and S7 measured strain trends are similar to the predicted strain. This indicates visible structural variations experienced at S4. For S8, the trend lines are significantly different, highlighting potential damage in the left wall.

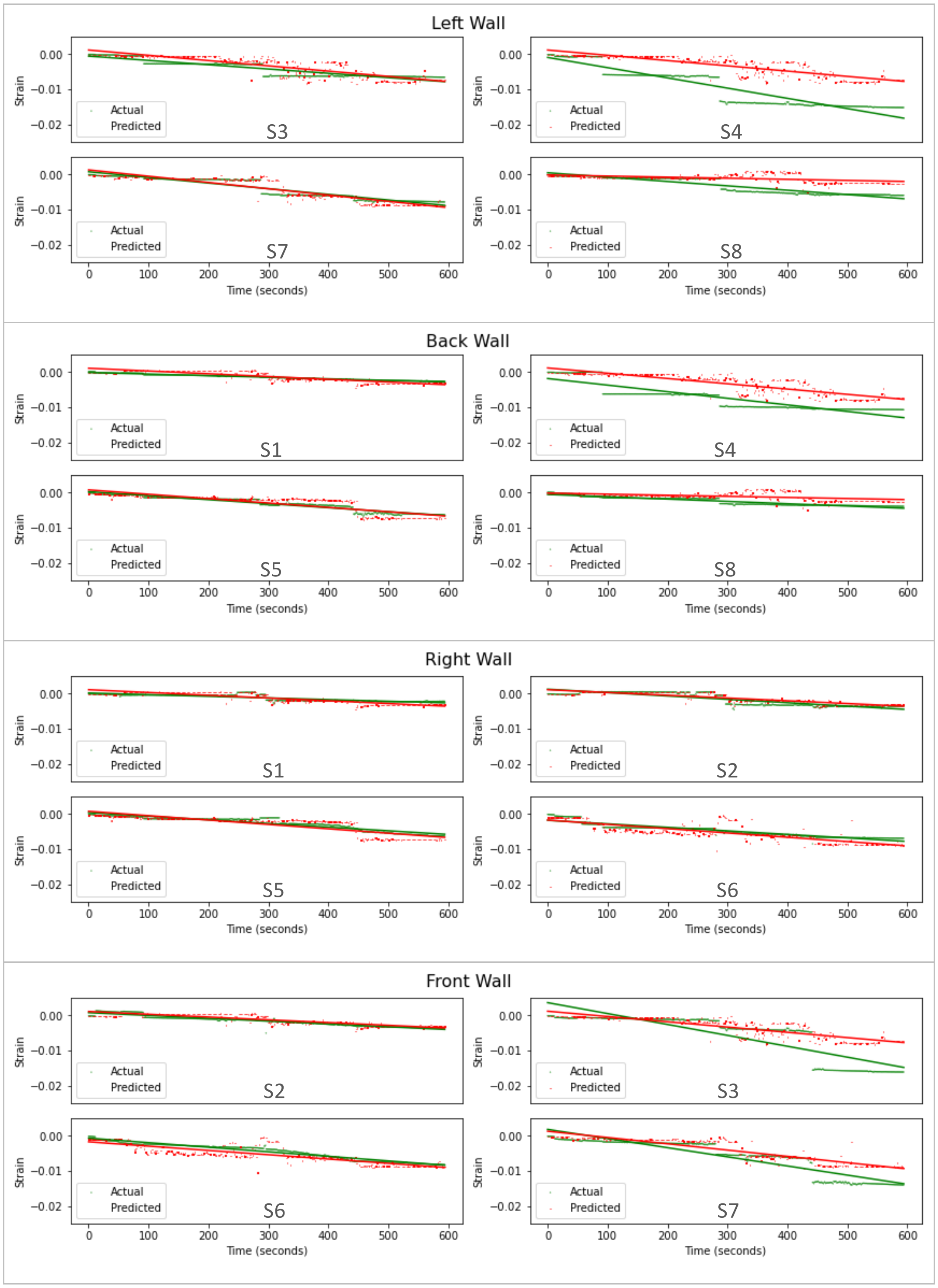


Figure 4-35. The measured strain and predicted strain trend line plots

Similarly, only the S8 and S4 sensor locations on the back wall highlight a significant variation in the trend line. The prediction and measured values trend lines for S1 and S5 are the same, showing no sign of damage. All the sensor locations on the right wall, S1, S2, S5, and S6, show the same trend lines for predicted and measured strains, indicating no structural condition variation or damage. For the front wall, the sensor locations S3 and S7 show clear differences in the trend line, indicating clear structural deformation near these sensor locations. However, the trend lines for S2 and S6 have no visible differences in the trends of predicted strain and measured sequences.

The overall damage assessment results for trend lines are the same as discussed with the actual raw measured strain plots. However, the trend line offers a clear visualization of variation for evaluating the overall structural variations. Therefore, trend evaluation can be more useful for decision-makers to get an easy, simple, and clear idea about the overall condition and damage. Still, a raw strain measured plot comparison is needed to understand the time of damage and pattern of variations.

4.4.4.1 Damage Level Assessment and Localisation

Apart from visual inspection of the predicted strain trends, the damage level is statistically determined using the damage indicator (DI_{c_i}), as given in Equations 3-11. This indicator helps compare and assess the damage level at each sensor installed location. Similarly, to further confirm the damage location on each wall, the x_{d_W} and y_{d_W} damage coordinates are determined using the Equations 3-12 and 3-13. The determined damage coordinates correspond to the standard coordinate system, where the bottom left corner of each wall is considered an origin with $x: 0, y: 0$ coordinations. The resulting DI_{c_i} for all the sensor locations and the coordinates of potential damage are given in Table 4-8.

The sensor locations S4 on the left wall sensed the highest level of damage (7.4), indicating critical damage at this point. All other sensor locations showed far lower damage levels than this location. Such damage variations across the wall strongly suggest that, while the damage is critical, it is most close to this location. The determined ($x_{d_{LW}} = 7.7cm, x_{d_{LW}} = 30.1cm$) damage coordinates on the left wall also strongly suggest that the damage location is at the corner of this wall. A similar case is for the back wall, which shows the highest damage (4.62) at S4, while all other damage levels are far lower than this location. Whereas the coordinates of the critical damage ($x_{d_{BW}} = 9.4cm, x_{d_{BW}} = 31.7cm$) also suggests the damage location near this corner. Thus, the adjacent wall corners showing damage confirm a corner failure type of damage.

Table 4-8. Damage indicators and coordinates.

Left Wall		**Back Wall**		**Right Wall**		**Front Wall**	
LW-S3	1.32	BW-S1	0.16	RW-S1	0.00	FW-S2	0.18
LW-S4	7.40	BW-S4	4.62	RW-S2	0.00	FW-S3	4.38
LW-S7	0.47	BW-S5	0.20	RW-S5	0.23	FW-S6	0.79
LW-S8	2.38	BW-S8	1.06	RW-S6	0.77	FW-S7	2.43
Coordinates							
$x_{d_{LW}}$	7.7	$x_{d_{BW}}$	9.4	$x_{d_{RW}}$	11.5	$x_{d_{FW}}$	20.1
$y_{d_{LW}}$	30.1	$y_{d_{BW}}$	31.7	$y_{d_{RW}}$	0.0	$y_{d_{FW}}$	23.5

For the right wall, all the sensor locations indicate very low values, suggesting no significant structural variation. Though such low variations do not indicate any damage, they may suggest minor intrinsic deformations, or in this case, these variations could be due to the heterogeneous properties of the wooden module. On the other hand, the front wall indicates a distinguished damage level for two sensor locations, S3 (4.38) and S7

(2.43). In contrast, the other two sensors on the front wall indicate a very low variation. Further calculation of damage coordinates ($x_{d_{FW}} = 20.1cm, x_{d_{FW}} = 23.5cm$) suggests a damage location between sensors S3 and S7.

4.4.5 Summary (Objective IV)

The study develops a robust hybrid deep learning model architecture for predicting the damage in the MiC module during logistic operations. The developed architecture integrates convolutional and sequential deep learning models to capture the higher-level complex relationships among the multiple sensor data streams. The convolutional model (CNN) effectively learns the relationship in various sensor data measurements at each timestep. In contrast, the sequential model learns the relationship across the time sequences at short and long periods. Thus, the hybrid model is able to predict the structural variations in the MiC module during the dynamic non-stationary logistic operations. The test results of the developed architecture reveal high efficiency for the predictions for all the model performance metrics: RMSE 1%, MAE 1%, R^2 96%, and Pearson Correlation Coefficient 98%. The field experiment, including the damaged module scenario, highlighted the developed model's efficiency for the unseen data.

The developed hybrid deep-learning model performance is at par with MiC module structural monitoring requirements. However, the developed architecture is trained and tested for a wooden module due to limited resources. Generally, a model working efficiently with noisy data, like wood material, should perform better for compact materials like concrete and steel. Still, validating the developed model with other representative materials is needed. The model training and validation data are also collected through a small field experiment in a relatively controlled environment. A real project field environment may have additional aspects and complexities, adding more variety to the logistics operation scenarios.

Chapter 5

CONCLUSIONS AND FUTURE RECOMMENDATIONS

5.1 Introduction

This research explores the dynamics, challenges, and technological solutions for improving the MiC logistic operations. MiC, being the latest construction approach and a relatively new research area, lacks critical knowledge related to its logistic operations. While being the bottleneck of a JIT assembly, the MiC logistics operations play a crucial role in the project performance. This strongly indicates the need to explore the dynamics of MiC logistic operations and technological solutions to meet the existing challenges. The research findings further adhere to the structural monitoring and damage assessment of the MiC modules during logistic operations for ensuring a seamless supply chain and JIT assembly.

In this context, the following objectives are determined to achieve the main aim of this study: (1) exploring the critical factors, their interrelationships, and mechanisms to influence the MiC logistics operations, (2) investigating the technologies suitable for MiC supply chain and explore the technological gap in addressing the MiC challenges, (3) develop an IoT based multi-sensing system to monitor the MiC module's structure during the logistic operations, (4) develop a hybrid deep learning model for robust damage predictions.

The relevant literature for each objective is reviewed and discussed in Chapter 2. Then, rigorous methods are adopted to achieve each one of these objectives. These methods are discussed in detail in Chapter 3. The detailed results of all objectives are discussed in Chapter 4.

5.2 Summary of the Findings

Objective 1: Exploring the factors influencing MiC logistics

This research first explored the factors influencing MiC's logistic operations and supply chain. Multiple research domains are explored extensively to identify a comprehensive set of influencing factors. The critical factors are identified using a rigorous eigenvector weighting approach based on factors abundance in the literature. Moreover, the influence of factors on each other is studied according to their co-occurrence in the literature. Then, factors are classified based on their influence using MICMAC analysis. The interactions among factors are investigated, and the influence mechanism of factors is realized to propose themes of factors.

The eigenvector-based ranking signifies the importance of factors based on the abundance of literature. However, it does not incorporate the individual interaction among factors and their strength of influence over the supply chain performance. Most top-ranked factors belong to the SCM category, as extensive literature has been published in this domain. The second most top-ranked factors belong to the information and knowledge management (IKS) category. Studies across all the research domains promote the information-related factors for an effective supply chain. However, MICMAC analysis results suggest that such factors have fewer connections with other SC factors. Generally, in the published literature, the factors related to the IKS and SCM are considered managerial. Therefore, past studies have mainly explored the interactions of these factors with administrative or organizational factors [193,233].

On the other hand, the logistics and site delivery factors are more influential in the MiC supply chain performance. For example, *module handling*, *flexible transportation*, and *inventory control* demonstrate strong influential relations with other supply chain factors. Similarly, the factors of site delivery, such as *assembling reworks*, *delays due to weather*, and *site layout*, are dynamically influencing the supply chain performance. It is because these factors occur at the supply chain's endpoint and control the flow, particularly in the case of JIT delivery. Moreover, factors related to natural causes, such as *logistics delays due to weather* and *natural hazards,* are autonomous and strongly impact the MiC supply chain performance. The identified themes of factors based on the combined analysis conclude this study's findings and demonstrate the influencing system of factors. The dominating factors define the influencing system's dynamics as input variables, while the symbiotic factors control the influence of the dominating factors. The external factors are autonomous and cannot be controlled but are managed by improving the positive impacts of symbiotic factors. The potential influencing factors are abundant in literature but are primarily studied in isolation.

Objective 2: Investigating the technologies for MiC logistic challenges

The second part of the study identifies the MiC supply chain challenges, critical Supply chain technologies, and their benefits and draws synergies between the technologies' benefits and MiC challenges. A powerful text analytical approach helped to effectively investigate the vast literature and identify the use and benefits of supply chain technologies. RFID, IoT, GPS, and Blockchain technologies are among the most popular technologies in supply chain studies. These technologies also address some of the MiC logistic challenges. For example, communication and coordination among supply chain stakeholders, delays due to installation errors, equipment breakdown and wrong module delivery, JIT delivery, etc.

On the other hand, some technologies are not being used to utilize their full potential in resolving supply chain issues. For example, tools like BIM and Digital Twin have vast capabilities to manage and organize multi-spectrum information at all levels of the supply chain. Thus, such tools can address several critical supply chain challenges. However, existing studies lack research on adopting such tools to address the most vital challenges. Similarly, several MiC challenges got limited attention and support from technologies, such as delays due to transportation issues, module handling, travel uncertainties, buffer space hedging, etc. The proposed framework incorporated technologies with vast potential to address several unattended MiC supply chain challenges comprehensively. This framework highlights that critical delays in the MiC supply chain may occur due to structural damages occurring in the MiC module structure during the logistics and supply chain operations. However, this vital challenge has not been addressed by any previously developed technological solutions.

Objective 3: Developing an IoT multi-sensing system

Therefore, the third part of the study developed a smart, integrated, portable, IoT-based multi-sensing system. The sensing devices in the system are designed to ensure its practicality for MiC logistics. A smaller form factor of sensing units is achieved to keep it practically invisible while installed on a module. The developed sensing system was calibrated by incorporating temperature compensation factors and turn-on bias elimination.

The sensing system performance is thoroughly tested in different conditions, and accuracy is comparable to standard commercial equipment like UTM.

The module's real-time structural condition monitoring enables early damage detection, allowing timely decisions to avoid supply chain disruptions. Also, it can improve the on-site safety inspection process while providing more insights into the module’s structural condition, increasing inspection speed, and highlighting the latent damages. Moreover, the safety of the real-time assembly process can be monitored. The sensing system provides detailed structural response data of logistic operations, which is useful for predicting the module's structural creep and forecasting maintenance during the building use phase. Thus, the system helps to ensure the JIT supply chain for MiC assembly, enhances assembly process safety, and helps to improve the module’s service life.

The application of the developed sensing system is demonstrated with a field experiment, and various analyses are presented to detect critical damage and assess the overall impact on the module’s health. The demonstrated field experiment evaluated the system's effectiveness and highlighted the efficacy of different sensors in determining the structural condition. The strain sensors are found to be more sensitive toward structural deformation and are directly helpful for determining the critical damage and its location. On the other hand, acceleration data is less sensitive but more helpful for assessing global structural deformations and overall structural health assessment. The gyroscope sensor's accuracy in predicting damage advocates its relevance but shows a complex relationship requiring deeper and more complicated analyses. Such insight can help understand the optimum number of sensing units required during the logistics and building use phases and the most suitable location for installing sensors.

The field experiment demonstrated several traditional methods for monitoring the module structural variation and assessing the damage, such as moving windows, histograms, FFT, etc. Although these conventional damage assessment methods can effectively monitor structural variations, they require intensive statistical analysis and data processing. Such requirements make these methods less reliable and suitable for real-time monitoring and quick decision-making, which are essential for MiC logistic operations.

Objective 4: Developing a hybrid deep learning model

A robust hybrid deep learning model architecture is developed in the final part of this study. The developed architecture integrates convolutional and sequential deep learning models to capture the higher-level complex relationships among the multiple sensor data streams. The convolutional model (CNN) effectively learns the relationship in various sensor data measurements at each timestep. In contrast, the sequential model learns the relationship across the time sequences at short and long periods. Thus, the hybrid model is able to predict the structural variations in the MiC module during the dynamic non-stationary logistic operations. The test results of the developed architecture reveal high efficiency for the predictions for all the model performance metrics: RMSE 1%, MAE 1%, R^2 96%, and Pearson Correlation Coefficient 98%. The field experiment, including the damaged module scenario, also highlighted the developed model's efficiency for the unseen data.

Overall, this study developed a complete and practical solution for the construction industry, especially for MiC projects. The project stakeholders, particularly contractors, can benefit from the developed multi-sensing IoT system and the deep learning model to monitor the structural health of the module and asses the damage before its arrival on the site. Such real-time information enables them to make timely decisions to avoid supply chain disruptions. Also, this system will ensure the module's safety during the assembly process.

5.3 Research Contributions

Overall, this research theoretically contributes to the structural health monitoring and prefabricated and modular construction and research domains. The findings of this research bridge the research gap in exploring modular construction supply chain dynamics and investigating its logistic operations. The outcomes of this study, in the form of frameworks, models and technologies, lead to enhanced productivity, safety, innovation, and sustainability in the construction industry. Further specific theoretical and practical contributions of all the research outcomes are summarised below.

5.3.1 Influencing factors of MiC logistics

This part of the research identifies the most critical influencing factors and their interrelationships to influence the supply chain. Considering influencing mechanisms, the factors are distributed into functional categories, highlighting (a) the core factors (dominating) responsible for supply chain performance, (b) factors playing a symbiotic role in transferring the effects on supply chain performance and (c) factors that need further investigation to explore their impact on the supply chain. These outcomes are highly beneficial for understanding the dynamics of MiC logistic operations and can be utilized by researchers and industry practitioners, such as:

- The identified factors' relationships and influencing mechanisms highlight the role and gravity of each factor in affecting the supply chain performance under any uncertainty.

- The highlighted core supply chain performance factors lead towards a larger framework for MiC supply chain performance assessment.
- The identified potential influencing factors offer new research directions for improving MiC supply chain performance.
- Industry practitioners can use the highlighted framework of influencing factors to improve supply chain policies and devise logistic strategies.
- Supply chain managers can improve supply chain productivity and sustainability by focusing on identified core dominating and symbiotic factors.

5.3.2 Technologies for MiC logistics

This study contributes to the body of knowledge by exploring the synergies between MiC challenges and existing technologies. The rigorous review and analyses conducted in this research highlight the (a) benefits and capabilities of existing technologies for supply chain and logistics management, (b) suitability of these technologies for MiC and (c) technology gaps in addressing the MiC challenges. (d) Meanwhile, the proposed technology adoption framework for the MiC module lifecycle structural monitoring introduces a novel research direction. Overall, the study highlights the current state of technology applications for the MiC supply chain and logistics operations and offers future directions. Meanwhile, it promotes technology adoption to enhance construction automation in MiC by highlighting the relevant technologies and their benefits. Also, the outcomes have very pertinent utilisation for research and industry:

- The identified technology gaps highlight MiC challenges that require immediate technology attention. Researchers can focus on these areas and develop innovations to improve MiC productivity and sustainability.
- The research elaborates on the suitability of technologies for MiC challenges. Thus, industry users can use this study to select the most suitable technology.

5.3.3 Multi-sensing IoT System

This research part develops an integrated multi-sensing technology for monitoring the module structure throughout its life cycle. In contrast to the previously existing structural health monitoring sensors, (a) the developed technology integrates multiple sensors in one portable device, (b) the device has a small form factor, making it perfectly suitable for MiC modules, (c) it incorporates short and long-range communication capabilities, making it suitable for remote area monitoring, (d) it incorporates novel communication protocols to handle large data transmission with negligible latency and data loss, and (e) it has powerful processing capabilities to handle on-device embedded deep-learning models.

Such a robust technology opens further avenues for MiC research and offers several industry applications:

- Multi-sensing logistics monitoring can provide large amounts of data from real-field scenarios. Such data will be highly beneficial in investigating the dynamics of MiC logistic operations. Such insights can help improve logistic strategies and the design of the MiC modules.

- Real-time structural monitoring offered by the developed sensing system enables proactive decision-making. Early decision-making can help improve the supply chain flow, save resources, and improve productivity.
- The sensing system offers detailed structural health assessment that can significantly improve the pre-assembly inspection process, consequently improving the assembly productivity, speed and safety.
- Meanwhile, it improves the construction quality of MiC buildings by providing a detailed structural assessment of newly built structures and enabling proactive and accurate maintenance schedules.

5.3.4 Deep Learning Damage Assessment

This study develops a hybrid integrated model for predicting the damage in the MiC module during logistic operations. The developed novel model architecture (a) integrates the convolutional (CNN) and sequential (GRU) deep learning models and (b) enables the sensor fusion of multivariate time-series data. Such an integrated model successfully modelled the correlations among the MiC module motion and structural variations during logistics operations. This developed model architecture contributes to the research by enabling the structural assessment of non-stationary structures. Also, it offers several benefits for MiC:

- It enables the structural monitoring of non-stationary structures by effectively capturing the correlation between motion and structural variations.
- This model improves the pre-assembly module inspection by offering detailed structural assessment and predicting critical damages. Consequently, it enhances

assembly speed, saves time, enhances quality and safety, and enables proactive maintenance.

5.4 Research Limitations

The first part of the research explores the influencing factors and discusses the prospective relationships of potential influencing factors with other SC factors. However, future studies should investigate their detailed mechanism influencing the MiC SC performance. Due to limited MiC SC literature, the study mainly explores the factors prevalent in MiC SC from the general SC and logistics management literature. Future researchers can collect more specific analytical information on MiC SC to analyze such influencing factors. Moreover, this study adopted the interpretive analysis approach through co-occurrence matrixes to analyze the MiC SC influencing factors, limiting this study's findings. In the future, empirical and analytical data on MiC SC factors should be collected to examine their influencing mechanism. The findings of this study are not limited to any country or region. However, further evaluation of identified factors can be performed to obtain region-specific results.

The developed IoT sensing system accurately assesses the structural response in real time. Although, it tried to address the issues related to the form factor and power consumption. Still, long-term power backup is impossible without increasing the sensing device's form factor. The integrated sensor accuracy is up to the standards and comparable with the standardized commercial equipment. However, simultaneously acquiring high-frequency data (above 200Hz) from multiple integrated sensors can compromise the sensed data quality. Though such limitation doesn’t affect the MiC module structural monitoring, other applications may require data above 200Hz. Also, in its current form, it lacks any water- and dustproofing; thus, using it for long periods may require maintenance and special supervision.

The developed hybrid deep-learning model performance is at par with MiC module structural monitoring requirements. However, the developed architecture is trained and tested for a wooden module due to limited resources. Generally, a model working efficiently with noisy data, like wood material, should perform better for compact materials like concrete and steel. Still, validating the developed model with other representative materials is needed. The model training and validation data are also collected through a small field experiment in a relatively controlled environment. A real project field environment may have additional aspects and complexities, adding more variety to the logistics operation scenarios.

5.5 Future Work and Recommendations

The potential improvements and recommendations for future research work are presented in this section. The suggested recommendations are categorized into two groups:

Enhancement of the existing research

The first objective successfully explored the influencing factors and their dynamics; however, the current research only extracts the factors and their impacts from the existing literature. Future studies can incorporate a more comprehensive approach based on the opinions of industrial experts to explore these factors. The comparison of such investigation with the current literature-based investigation can provide interesting propositions. Similarly, for investigating the benefits of technology, technology user opinions should be incorporated to get an additional perspective compared to the literature.

The IoT sensing device can be further developed to enhance its robustness and reliability and improve its practicality. Further sensor optimization and circuit integration can be improved to reduce its power consumption while maintaining the form factor. A more detailed integrated circuit design, where individual supporting components of each sensor are integrated into a single circuit, can help achieve a further reduced form factor and power consumption. In this context, further optimization of the sensing device's programming algorithm can also help improve power consumption. In addition, such optimization can also help increase the frequency of data acquisition, enabling its application for other uses. In its current form, the developed sensing device requires careful and supervised installation. Improving its casing design to add the water- and dust-proofing features will make it more robust and rigid for commercial uses.

Moreover, the developed deep learning architecture is demonstrated using a wooden module for cost-effectiveness. Validating the developed model with other representative materials is required to ensure model generalizability.

Extension of the existing research

The findings of the first part of the study provide valuable considerations in the form of themes and factors influencing behaviour. However, future research can elaborate more on understanding the effect of factors on SC performance across different phases. Thus, practitioners can effectively consider the critical factors when devising strategies during the planning phase. For instance, the impact of harmful external factors can be influenced by effectively managing symbiotic factors. Also, the dominating factors have a core effect and can impact the SC at multiple levels. Therefore, considering the critical influencing factors and their relations, a detailed framework can be developed for devising MiC supply chain and logistic strategies.

Additionally, relying on the identified factors, a MiC supply chain performance mechanism can be evaluated further to improve the MiC SC operations. Moreover, a group of factors, potential influencing factors, needs further exploration. The results of the investigation of technologies suggested a comprehensive framework for the lifecycle module structural monitoring by integrating the sensing system data with a digital twin. The current research focused on the development of the sensing system. In the future, the developed sensing system can be integrated with a digital twin to enable lifecycle structural monitoring of MiC modules.

Further experimentation and analyses should be performed to analyze the behaviour of the accelerometer, gyroscope, and strain in different scenarios of MiC logistic operations, which can help to understand their efficiency in structural variation assessment. Such analysis can lead to the development of more robust structural assessment models. Additionally, a simulation of MiC logistics scenarios can be performed to identify the critical locations on the module. Consequently, a more accurate and rationalized sensing device installation location can be determined. It can also reduce the number of sensing devices required for each module and improve the damage assessment.

The developed hybrid deep-learning model integrates the convolutional and sequential models to achieve the best results. Future studies can enhance this approach further by incorporating an additional model for data enhancement, such as generative networks, to improve the model's generalisability and performance in unseen scenarios. Similarly, detailed data representing the logistic scenarios can be simulated using structural simulation software. Such an approach can help to incorporate the additional logistics scenarios and enhance the model performance.

APPENDICES

Appendix – A. Scientometrics extracted from studies

No.	Studies	Source Title	Research Domain	Research Focus	Type of Factors
1	Power, et al. [243]	International Journal of Physical Distribution and Logistics Management	General SC	Flexibility and Agility	SC Success Factors
2	Ngai, et al. [220]	Production Planning & Control	General SC	IT Tools	SC Success Factors
3	[193]	Information and Management	General SC	Information and Knowledge management	SC Success Factors
4	Tarokh and Soroor [298]	2006 IEEE International Conference on Service Operations and Logistics, and Informatics	General SC	Information and Knowledge management	SC Barriers and Failures
5	Zhang and Dhaliwal [363]	International Journal of Production Economics	General SC	SC Performance	SC Influencing Factors

6	Hu and Hsu [140]	Management Research Review	General SC	Sustainability and Green SC	SC Risk factors
7	Lu [190]	Applied Mechanics and Materials	General SC	Risk and Uncertainty	SC Influencing Factors
8	Duan, et al. [83]	Asia-Pacific Journal of Operational Research	Construction	SC Performance	SC Success Factors
9	Lao, et al. [172]	Measuring Business Excellence	Logistics	SC collaboration and 3PL	SC Influencing Factors
10	Meidute and Raudeliuniene [210]	Business: Theory and Practice	Logistics	SC Performance	SC Influencing Factors
11	Shukor, et al. [269]	Association of Researchers in Construction Management, ARCOM 2011 - Proceedings of the 27th Annual Conference	Construction	SC Performance	SC Barriers and Failures
12	Huam, et al. [142]	African Journal of Business Management	General SC	SC Performance	SC Success Factors
13	Kim and Rhee [169]	International Journal of Production Research	General SC	Sustainability and Green SC	SC Success Factors

14	Zhang and Wang [365]	Applied Mechanics and Materials	Logistics	SC Performance	SC Influencing Factors
15	Liu, et al. [185]	Applied Mechanics and Materials	General SC	Sustainability and Green SC	SC Influencing Factors
16	Li and Bian [179]	Advanced Materials Research	General SC	SC Performance	SC Influencing Factors
17	Patil and Kant [237]	IEEE International Conference on Industrial Engineering and Engineering Management	General SC	Information and Knowledge management	SC Success Factors
18	Mothilal, et al. [217]	International Journal of Production Research	Logistics	SC collaboration and 3PL	SC Success Factors
19	Shen [264]	ICLEM 2012	Logistics	SC collaboration and 3PL	SC Influencing Factors
20	Patil and Kant [237]	IEEE International Conference on Industrial Engineering and Engineering Management	General SC	Information and Knowledge management	SC Success Factors

21	Liu [187]	Lecture Notes in Electrical Engineering	General SC	Risk and Uncertainty	SC Influencing Factors
22	Zhang, et al. [364]	Applied Mechanics and Materials	General SC	SC Performance	SC Influencing Factors
23	Singh [272]	Measuring Business Excellence	General SC	SC collaboration and 3PL	SC Influencing Factors
24	Anand, et al. [19]	Applied Mechanics and Materials	General SC	Sustainability and Green SC	SC Influencing Factors
25	Anand, et al. [20]	Applied Mechanics and Materials	General SC	Sustainability and Green SC	SC Influencing Factors
26	Malviya and Kant [198]	IEEE International Conference on Industrial Engineering and Engineering Management	General SC	Sustainability and Green SC	SC Influencing Factors

27	Patil and Kant [238]	Journal of Modelling in Management	General SC	Information and Knowledge management	SC Success Factors
28	Masood, et al. [204]	Sustainable Cities and Society	Construction	SC Performance	SC Success Factors
29	Avelar-Sosa, et al. [30]	Journal of Applied Research and Technology	General SC	Risk and Uncertainty	SC Influencing Factors
30	Vilko, et al. [316]	Procedia-Social and Behavioral Sciences	General SC	SC collaboration and 3PL	SC Risk factors
31	Saen [253]	Acta Polytechnica Hungarica	Logistics	SC collaboration and 3PL	SC Influencing Factors
32	Rikalovic and Cosic [249]	Acta Polytechnica Hungarica	General SC	SC Performance	SC Influencing Factors
33	Mello, et al. [211]	International Journal of Operations and Production Management	Construction	SC collaboration and 3PL	SC Influencing Factors

34	Behera and Mukherjee [37]	International Journal of Information Systems and Supply Chain Management	General SC	SC collaboration and 3PL	SC Influencing Factors
35	Talib, et al. [294]	EuroMed Journal of Business	General SC	SC Performance	SC Success Factors
36	Fu, et al. [103]	International Journal of Logistics Management	Logistics	IT Tools	SC Influencing Factors
37	Sangari, et al. [257]	Measurement	General SC	Flexibility and Agility	SC Success Factors
38	Singh [271]	Journal of Manufacturing Technology Management	General SC	Flexibility and Agility	SC Influencing Factors
39	Gandhi, et al. [105]	International Journal of Logistics Research and Applications	General SC	Sustainability and Green SC	SC Success Factors
40	Singh, et al. [274]	Competitiveness Review	General SC	Sustainability and Green SC	SC Barriers and Failures
41	Sangari, et al. [256]	International Journal of Industrial and Systems Engineering	General SC	Flexibility and Agility	SC Success Factors

42	Malviya, et al. [199]	International Journal of Logistics Systems and Management	General SC	Sustainability and Green SC	SC Success Factors
43	Vishvakarma and Sharma [317]	Proceedings of the International Conference on Industrial Engineering and Operations Management	General SC	IT Tools	SC Influencing Factors
44	[28]	International Journal of Supply Chain Management	Construction	SC Performance	SC Success Factors
45	Singh, et al. [273]	Journal of Modelling in Management	General SC	Flexibility and Agility	SC Influencing Factors
46	Chiappetta Jabbour, et al. [59]	Production Planning and Control	General SC	Sustainability and Green SC	SC Success Factors
47	Meidute and Raudeliuniene [210]	International Journal of Business Excellence	Logistics	SC collaboration and 3PL	SC Influencing Factors
48	Ab Talib and Muniandy [1]	World Applied Sciences Journal	Logistics	Sustainability and Green SC	SC Success Factors
49	Song, et al. [283]	Journal of Cleaner Production	General SC	Sustainability and Green SC	SC Risk factors

50	Zailani, et al. [356]	Review of Managerial Science	Logistics	SC collaboration and 3PL	SC Influencing Factors
51	Abdullah and Nasir [3]	Malaysian Construction Research Journal	Construction	SC Performance	SC Barriers and Failures
52	[289]	The Journal of Asian Finance, Economics and Business	General SC	SC collaboration and 3PL	SC Influencing Factors
53	Wibowo, et al. [326]	Journal of Industrial Engineering and Management	Construction	Sustainability and Green SC	SC Success Factors
54	Sandeepa and Chand [255]	Uncertain Supply Chain Management	General SC	Sustainability and Green SC	SC Influencing Factors
55	Grine, et al. [118]	Proceedings of the International Conference on Industrial Engineering and Operations Management	Logistics	SC Performance	SC Influencing Factors
56	Sureeyatanapas, et al. [291]	Journal of Cleaner Production	General SC	Sustainability and Green SC	SC Influencing Factors

57	Gupta, et al. [122]	Vision	General SC	SC collaboration and 3PL	SC Success Factors
58	Bienhaus and Haddud [40]	Business Process Management Journal	General SC	IT Tools	SC Barriers and Failures
59	Fauzi, et al. [100]	IOP Conference Series: Materials Science and Engineering	Construction	SC Performance	SC Barriers and Failures
60	Oláh, et al. [226]	Polish Journal of Management Studies	Logistics	SC collaboration and 3PL	SC Influencing Factors
61	Yan, et al. [343]	The Engineering Economist	General SC	IT Tools	SC Influencing Factors
62	Ghafourian and Shirouyehzad [109]	International Journal of Services and Operations Management	General SC	Sustainability and Green SC	SC Success Factors
63	Wuni, et al. [334]	International Journal of Construction Management	Construction	Risk and Uncertainty	SC Influencing Factors
64	Mehdi and Ahmed [206]	International Journal of Logistics Systems and Management	General SC	SC Performance	SC Influencing Factors

65	Onstein, et al. [229]	Transport Reviews	General SC	SC Performance	SC Influencing Factors
66	Pan, et al. [233]	International Journal of Logistics Management	General SC	Information and Knowledge management	SC Influencing Factors
67	Pan, et al. [233]	International Journal of Quality and Reliability Management	General SC	SC Performance	SC Influencing Factors
68	Meng, et al. [212]	IEEE International Conference on Industrial Engineering and Engineering Management	General SC	Sustainability and Green SC	SC Influencing Factors
69	ŞENOL, et al. [261]	Politeknik Dergisi	General SC	SC Performance	SC Influencing Factors
70	Sharma, et al. [263]	Clean Technologies and Environmental Policy	General SC	Sustainability and Green SC	SC Influencing Factors
71	Abas, et al. [2]	International Journal of Construction Management	Construction	Risk and Uncertainty	SC Success Factors

72	Yadav and Singh [342]	Resources, Conservation and Recycling	General SC	IT Tools	SC Influencing Factors
73	Prasad, et al. [244]	Transportation Research Procedia	General SC	Sustainability and Green SC	SC Influencing Factors
74	Correia, et al. [66]	Journal of Engineering, Design and Technology	Construction	SC Performance	SC Influencing Factors
75	Yazdi, et al. [351]	International Journal of Logistics Systems and Management	Logistics	Sustainability and Green SC	SC Success Factors
76	Wuni, et al. [335]	International Journal of Construction Management	Construction	Risk and Uncertainty	SC Influencing Factors
77	Karamasa, et al. [160]	Decision Making: Applications in Management and Engineering	Logistics	SC collaboration and 3PL	SC Influencing Factors
78	[241]	Proceedings of the International Conference on Industrial Engineering and Operations Management	Logistics	SC collaboration and 3PL	SC Success Factors

79	Alsadi, et al. [14]	International Journal of Information Systems and Supply Chain Management	General SC	IT Tools	SC Influencing Factors
80	Yang, et al. [349]	Environment, Development and Sustainability	General SC	Sustainability and Green SC	SC Influencing Factors
81	Ekanayake, et al. [88]	Engineering, Construction and Architectural Management	Construction	SC Performance	SC Success Factors
82	Hussein and Zayed [148]	Journal of Cleaner Production	Construction	SC Performance	SC Success Factors
83	Nilsson and Göransson [223]	Journal of Cleaner Production	General SC	Sustainability and Green SC	SC Success Factors
84	Ahmed Khan, et al. [8]	IEEE Transactions on Engineering Management	General SC	SC transformation	SC Success Factors
85	Ekanayake, et al. [87]	Engineering, Construction and Architectural Management	Construction	SC Performance	SC Success Factors
86	Alomari [13]	Uncertain Supply Chain Management	General SC	SC Performance	SC Success Factors

87	Yadav and Samuel [341]	Journal of Modelling in Management	General SC	SC Performance	SC Influencing Factors
88	Chai and Li [56]	Tehnički vjesnik	General SC	IT Tools	SC Influencing Factors
89	Dang, et al. [71]	The Journal of Asian Finance, Economics and Business	Logistics	SC collaboration and 3PL	SC Influencing Factors
90	Thai, et al. [304]	International Journal of Logistics Management	Logistics	SC collaboration and 3PL	SC Success Factors

Appendix – B. Factors occurrence in studies

No.	Studies	IKS1	IKS2	IKS3	IKS4	IKS5	IKS6	Log1	Log2	Log3	Log4	Log5	Log6	Log7	Log8	Log9	Log10	Log11	SCM1	SCM2	SCM3	SCM4	SCM5	SCM6	SCM7	SCM8	SCM9	SCM10	M1	M2	M3	M4	M5	M6	M7	M8	S1	S2	S3	S4	S5	S6	S7	S8
1	Power, et al. [243]																																											
2	Ngai, et al. [220]												x										x																					
3	[193]	x																		x																								
4	Tarokh and Soroor [298]				x							x							x							x											x							
5	Zhang and Dhaliwal [363]					x											x																											
6	Hu and Hsu [140]						x												x	x	x		x											x										
7	Lu [190]																																											
8	Duan, et al. [83]																							x				x				x												
9	Lao, et al. [172]																x	x			x							x	x	x			x											
10	Meidute and Raudeliuniene [210]					x																																						

11	Shukor, et al. [269]						x		x		x																															
12	Huam, et al. [142]										x	x	x	x	x				x															x			x		x			
13	Kim and Rhee [169]					x							x		x				x																							
14	Zhang and Wang [365]						x																																			
15	Liu, et al. [185]																																									
16	Li and Bian [179]												x		x				x																							
17	Patil and Kant [237]					x		x	x	x													x					x	x	x	x	x	x		x	x		x	x	x	x	x
18	Mothilal, et al. [217]																		x	x																						
19	Shen [264]								x		x								x											x							x					
20	Patil and Kant [237]				x												x		x								x															
21	Liu [187]																																									
22	Zhang, et al. [364]	x					x																																			

23	Singh [272]	x			x															x		x						x											
24	Anand, et al. [19]																			x		x						x	x				x						
25	Anand, et al. [20]																			x														x			x		
26	Malviya and Kant [198]												x										x																
27	Patil and Kant [238]																																	x					x
28	Masood, et al. [204]																											x											
29	Avelar-Sosa, et al. [30]				x	x	x																																
30	Vilko, et al. [316]																											x		x									
31	Saen [253]																x																x						
32	Rikalovic and Cosic [249]						x																																
33	Mello, et al. [211]																																	x					
34	Behera and Mukherjee [37]					x														x	x						x	x											

35	Talib, et al. [294]												x	x					x																x						
36	Fu, et al. [103]	x											x															x					x						
37	Sangari, et al. [257]									x						x							x								x						x			x
38	Singh [271]				x																							x		x										
39	Gandhi, et al. [105]																																							
40	Singh, et al. [274]	x	x			x											x				x	x																		
41	Sangari, et al. [256]	x																		x																				
42	Malviya, et al. [199]					x																x																		
43	Vishvakarma and Sharma [317]				x		x																																	
44	Asri, et al. [28]												x																											
45	Singh, et al. [273]																																							
46	Chiappetta Jabbour, et al. [59]													x					x																x						

47	Meidute and Raudeliuniene [210]																																											
48	Ab Talib and Muniandy [1]				x																				x																		x
49	Song, et al. [283]	x																				x						x																
50	Zailani, et al. [356]										x									x		x				x		x																
51	Abdullah and Nasir [3]			x						x									x									x		x	x						x			x				
52	Suong [289]																																											
53	Wibowo, et al. [326]																																				x							
54	Sandeepa and Chand [255]										x	x											x																					
55	Grine, et al. [118]				x																						x																	
56	Sureeyatanapas, et al. [291]				x		x																																					
57	Gupta, et al. [122]						x																																					

58	Bienhaus and Haddud [40]										x							x																x				
59	Fauzi, et al. [100]																																				
60	Oláh, et al. [226]																					x						x									
61	Yan, et al. [343]	x											x																								
62	Ghafourian and Shirouyehzad [109]										x			x																							
63	Wuni, et al. [334]				x												x		x								x							x			
64	Mehdi and Ahmed [206]		x									x																									x
65	Onstein, et al. [229]																																				
66	Pan, et al. [233]																																				
67	Pan, et al. [233]	x	x																x			x	x					x									
68	Meng, et al. [212]	x			x								x										x														x
69	ŞENOL, et al. [261]	x																				x															

70	Sharma, et al. [263]																																					
71	Abas, et al. [2]																				x																	
72	Yadav and Singh [342]	x	x																																			
73	Prasad, et al. [244]																					x							x									
74	Correia, et al. [66]				x	x																																
75	Yazdi, et al. [351]						x																x															
76	Wuni, et al. [335]					x	x																															
77	Karamasa, et al. [160]			x							x																											
78	[241]										x											x	x															
79	Alsadi, et al. [14]																																					
80	Yang, et al. [349]				x						x	x					x		x	x	x	x			x	x								x				x
81	Ekanayake, et al. [88]																																		x			x

82	Hussein and Zayed [148]																																											
83	Nilsson and Göransson [223]	x	x						x		x	x							x					x	x	x		x	x	x				x									x	x
84	Ahmed Khan, et al. [8]			x				x	x	x																		x	x		x				x		x			x	x			x
85	Ekanayake, et al. [87]																																											
86	Alomari [13]				x			x		x						x				x											x			x		x				x		x	x	x
87	Yadav and Samuel [341]				x															x																								
88	Chai and Li [56]				x																																							
89	Dang, et al. [71]					x															x																							
90	Thai, et al. [304]					x																				x																		

Appendix – C. Technologies chains of action for delivering benefits

Benefit's Chains of Action	References
<u>Blockchain</u>	
Blockchain > trust-free, transparency, pseudonymity, democracy, automation, decentralization, and security	[338]
Smart contracts > automated transaction generation, decision-making, and data storage	[338]
Blockchain > delivery reliability; mass customization > increasing profitability of manufacturing organizations	[161]
Blockchain > savings in transaction costs, audit costs, paper costs, verification costs, networking costs, R&D costs, and costs of contracting	[161]
Blockchain > Ensuring simplified audits	[161]
Blockchain > removal of nonvalue-adding intermediaries> reduce waste > improves SC leanness	[161]
Blockchain > ensuring direct access to a more significant number of stakeholders through connected blockchain networks	[161]
Blockchain > Effectively Deterring fraudulent identities and products	[161]
Blockchain > information about products/transactions traceable to the point of origin	[161]
Blockchain > Ensuring data integrity for collaborative computer-aided design (CAD) environments	[176,180]
Blockchain > facilitating security, liability, transferability, and live data collection in BIM projects	[180,222]
Blockchain > efficient storage of project documentation > trustworthy infrastructure for information management during all building lifecycle stages	[180,313]

Blockchain > efficient storage of product data related to the source, characteristics, manufacturing, shipping, installation, and maintenance > contributing to the circular economy	[180,267]
Blockchain > simplify and integrate economic, information, and material flows > speed up construction processes; combat delivery failures, delays, and withheld payments	[168,180]
Smart contracts > Solving interim payment issues in construction projects	[6,61,74,339]
Blockchain > traceability of construction project quality	[265,339,370,372]
Blockchain > efficient information flow management	[240,339]
Smart contracts > reducing paperwork, instant payment, secured payments, lower transaction costs, and increased trust between partners	[7,70,203,321,339]
RFID	
RFID tags for heat sensing > detecting heat exposures in supply chains; transportation mishandling of heat-sensitive items	[32]
RFID > track proximity of construction workers and equipment operators > effective safety alert system	[85,300]
RFID>workable in a dusty or muddy environment	[191]
RFID > real-time tracking; safety monitoring; efficient warehouse operations > increased Supply Chain efficiency > increase in sales volumes; improved profitability for suppliers and retailers	[43,208]
RFID > detecting tampering and potential theft; spoilage or damage of goods > safety and security of merchandise	[44,208]
RFID > efficient management of short shelf-life goods, container transport, and automated delivery tracking system	[162,201,208,281]

RFID > ensure quality control during production	[162,201,208,281]
RFID > tracing the precise location of tagged materials on construction sites	[208,281]
RFID > detecting and flagging damaged products	[123,208]
RFID > contributing to smart packaging, automatic checkout, smart appliances, smart recycling, and marketing	[63,155,208]
RFID > improves security, productivity, inventory control, and traceability and results in capital and operational savings	[63,155,208]
RFID > results in capital and operational savings	[63,155,208]
RFID > reducing labor costs, claims, and returns > reducing operating costs	[208]
RFID > efficient goods receiving, stocking, and maintenance	[132]
RFID > mitigating adverse effects of inventory misplacement	[50]
RFID > real-time traceability and visibility > supporting just-in-time, lean/responsive manufacturing, and mass customization.	[126,144]
RFID + 4D-CAD > supporting logistics and progress management	[60,191]
RFID > enhancing construction quality inspection and management	[191,322]
RFID > efficient precast production management system	[191,352]
RFID > track construction assets	[115,154,191]
RFID > tracking the 3D location of buried assets	[84,191]
RFID > efficient on-site inspection support system	[82,191]
RFID > track depth of piles; identify anti-counterfeit materials > improve construction quality	[191]

RFID > efficient management of C&D waste	[191]
RFID tags in safety gears > improving safety conformance on construction sites.	[191]
RFID-enabled safety precaution system > informing workers of potential risks on site	[191]
RFID > tracks machines, help regulate machine operation, and help manage the maintenance records > Efficient management of machinery	[191]
RFID > reduction of the lead times of various activities, including inbound logistics, storage, pick, and dispatch products > reduces warehouse costs.	[319]
RFID > enabling real-time traceability information > improving decision making > Improvement of Customer Relationship Management	[319]
RFID > enabling real-time traceability information > Improved recall management	[319]
RFID > cost saving in construction supply chains	[77]
RFID > efficient inventory management in warehouses	[17,340]
RFID > automated data collection; assurance of data dependencies; improvements in production and inventory visibility > help achieve leaner manufacturing	[45]
RFID in production system > enabling real-time information about the parts included in the system > improving production efficiency and reducing costs	[213]
RFID in production system > helping decentralize the system information > flexible and agile production process	[213]
RFID > tracking site access of construction workers > efficient and accurate access control and labor attendance record system	[85,191]
<u>Barcode</u>	

barcode + GPS > identify and locate items	[282,323]
barcode use on construction sites > cost savings	[323]
barcode use > monitoring material flow in manufacturing enterprises	[52]
Heat and Temperature sensors	
Heat sensors in wearable technology > detect heat-stress conditions of construction workers > generate early warnings > improve health and safety	[85,86]
Heat sensors in confined spaces > Monitoring space temperature > improve health and safety	[85,248]
Heat sensors in food containers > Monitoring space temperature > Helping ensure product quality	[354]
Heat sensors in wearable technology > measure physical exertion and fatigue in construction workers > generate early warnings > improve health and safety	[27,121,174,314]
GPS	
Barcode + GPS > material and equipment tracking > reduction in construction waste	[85]
RFID + GPS > track construction site resources	[21,85]
GPS > measuring Labor activity	[85,156]
GPS > automated tracking of construction equipment	[85]
GPS > automated tracking of vehicles on construction site > helping avoid accidents	[85,227]
GPS > proximity analysis > determining risks on job sites	[85,247]
GIS > providing shortest routes of material delivery > contributing to Construction Supply Chain Management	[78]

IoT	
IoT > increased efficiency in assembly systems	[323]
IoT > increased efficiency, safety, and security of operations related to warehousing, transportation, and last-mile delivery > improved logistics	[164]
IoT > agile and convenient management of merchandise (including foods) > solving food safety problem	[188]
IoT > efficient shop floor material control system	[323]
Wireless Network	
Wireless Network + Heat Sensors > communicating temperature information of food products > preventing food losses and wastage	[23]
Distance and Proximity sensor	
Distance and Proximity sensors > material handling in the warehouse; indoor transportation in the warehouse	[230]
Lidar and Laser scanning	
Laser scanning > generates as-built information about a building	[69]
Laser scanning > detecting and recording dimensions and smoothness of prefabricated products > quality performance	[192]
Laser scanning > generate as-built information of a building > record as-built information in BIM model > identify differences in building execution from design	[10]
Photogrammetry	
Photogrammetry > generate as-built information	[69]

Photogrammetry > track the real-time status of prefabricated components > ease in making managerial decisions; calculating the remaining time to the site; assessing the quality of production; improving lead time of responding to changes	[184]
Photogrammetry > identification of defective prefabricated units	[184]
Photogrammetry > generate BIM models of existing buildings	[69]
Photogrammetry > monitoring live progress of project schedule	[10]
Accelerometer > Monitoring fatigue of construction workers	[174,200]
Accelerometer > measuring vibrations experienced by prefabricated modules during transportation > ensuring safe transportation	[183]
Computer vision	
Machine Learning> monitor construction progress using 4D BIM; automate rule checking within BIM models; automate as-built 3D reconstruction using computer vision; monitor construction performance using still images	[99,124,125,236,279,280,344]
Computer vision > Identify and distinguish construction equipment	[85,293]
BIM	
BIM + RFID > progress monitoring of construction projects; facility management	[85,216]
BIM > improved design coordination; knowledge sharing among relevant actors	[31,173]
BIM > visualization for clash detections; controlling and scheduling capabilities > facilitating construction operations	[31,173]
BIM > time reduction; better communication; improved coordination > lower project costs; reduced project information-related issues	[46,235]

BIM > SC actors' collaboration; early joint decision-making among SC actors; collaborative planning and operations > enhancing performance of mechanical, engineering, and plumbing trades in construction projects	[9,173]
BIM > consistent project information sharing > stronger SC partnerships; improving trust among SC actors	[173]
<u>Digital Twin</u>	
digital twins > depict processes in simulation models > optimize processes > streamline and increase productivity of production processes	[288]
Digital twins > depict processes in simulation models > identify bottlenecks in production; identify shortcomings in systems > help improve systems based on previous performance data	[288]
digital twins > enhance construction productivity	[183]
IoT + BIM > Digital Twin for construction projects	[183]
Digital Twin> monitoring construction resources and progress	[178,183]
Digital Twin> occupational health and safety management	[159,183]
Digital Twin> Construction logistics and supply chain management	[183,373]
Digital Twin> Facility management	[58,183]

Appendix – D. Synergies between technologies and MiC logistics challenges

Benefits **Challenges**	Overproduction	JIT Production	Module handling	Transit storage location	Buffer space hedging	Route and vehicle selection	cross-border regulations	local traffic management	Travel uncertainties	Delays due to equipment breakdown	Delays due to bad weather and wind	Delays due to transportation issues	Delays due to wrong module	Delays due to installation errors and	Resource wastage during recurring	Transportation and storage	Communication and coordination	**References**
<u>Blockchain</u>																		
Enhanced security, trust, pseudonymity, transparency, and data integrity							x						x				x	[7,70,176,180,203,313,321,338,339]
automated transaction generation, decentralized decision-making, and data storage																	x	[176,180,338]
Reduced transaction costs, audit costs, paper															x			[7,70,161,203,321,339]

costs, verification costs, networking costs, R&D costs, and contracting costs; removal of nonvalue-adding intermediaries			
Direct and real-time access data sharing and collaboration with stakeholders		x	[161,176,180,222]
Effectively deterring fraudulent products and Identities	x		[161]
trustworthy information management during all building lifecycle stages		x	[180,240,313,339]
traceability of construction project quality			[161,265,339,370,372]
IoT			

increased efficiency in assembly systems																	x	[323]
increased efficiency, safety, and security of operations related to warehousing, transportation, and last-mile delivery		x							x	x	x	x						[164]
agile and convenient management of merchandise	x																	[188]
<u>RFID</u>																		
real-time tracking of workers for safety monitoring										x								[43,191,208]
efficient warehouse operations	x																	[17,85,300,319,340]
detecting tampering and potential theft																		[44,208]
safety and security of merchandise														x				[44,208]

Goods tracking and traceability throughout the delivery process			x		x		[162,201,208,281]
detecting damaged or spoiled products	x						[44,123,162,201,208,281]
Smart packaging, auto-checkout			x		x		[63,155,208]
inventory control, real-time traceability of raw materials	x	x					[50,63,115,132,154,155,191,208,281,319,352] [282,323]
reducing operating costs and wastage				x			[63,155,191,208] [213,323]
Enabling just-in-time, lean, and agility		x					[45,52,77,126,144,213]
Enhanced logistics management						x	[60,82,191]
Improved quality control							[191,322]
tracking the hidden parts or buried assets							[84,191]

efficient human resource management					[85,191]
Heat and Temperature sensor					
Detect heat-stress conditions of construction workers					[85,86]
Heat sensing in confined spaces to monitor health and safety					[27,85,121,174,248,314]
food condition monitoring in containers					[354]
GPS					
material and equipment location tracking	x		x		[85] [21,85]
measuring Labor activity				x	[85,156]
automated monitoring of construction sites to		x			[85,227] [85,247]

avoid clashes and accidents among moving equipment			
Optimum vehicle routing for material delivery	x		[78]
Accelerometer			
measuring vibrations experienced by prefabricated modules during transportation, ensuring safe transportation		x	[183]
Distance, Proximity sensor			
handling the manufacturing, warehouse, and indoor transportation to avoid equipment or good clash		x	[230]
Photogrammetry			

Generate as-built information			x	[69]
Assessing the quality of production, improving lead time of responding to changes	x		x	[184]
identification of defective prefabricated units			x	[184]
Generate BIM models of existing buildings				[69]
monitoring real-time progress of project schedule				[10]
Monitoring fatigue of construction workers				[174,200]
LIDAR, Laser scanning				
generates as-built information about a building				[69]

detecting and recording dimensions and smoothness of prefabricated products		x	[192]
Generate and record as-built information of a building in the BIM model, identify differences in building execution from design		x	[10]
CV			
monitor construction progress using 4D BIM; automate rule checking within BIM models; automate as-built 3D reconstruction using computer vision; monitor construction performance using still images			[99,124,125,236,279,280,344]

Identify and distinguish construction materials, and equipment		x		[85,293]
progress monitoring of construction projects, facility management				[85,216]
BIM				
improved design coordination, knowledge sharing among relevant actors				[31,173]
visualization for clash detections, controlling and scheduling capabilities, facilitating construction operations	x			[31,173]
time reduction, better communication, improved coordination, lower project costs, reduced project			x	[46,235]

information-related issues		
enhancing performance of mechanical, engineering, and plumbing trades in construction projects		[9,173]
stronger SC partnerships; improving trust among SC actors	x	[173]
Digital Twin		
streamline and increase the productivity of production processes	x	[288] [183]
Identify shortcomings in systems		[288]
monitoring construction resources and progress		[178,183]
occupational health and safety management		[159,183]

Enhanced facility management	[58,183]

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