Engineering Informatics and Digital Transformation

https://eidtrans.org

Schedule Control with Automated Progress Monitoring in Modular Construction Sites: Controlled Experiment

Nora H. Thompson[1,*], Sabine Schmid[2], Joseph N. Wright[1]

[1] Department of Civil and Environmental Engineering, Newark College of Engineering, New Jersey Institute of Technology, Newark, New Jersey, 07102, USA
[2] Department of Computer Science, Faculty of Engineering, University of Freiburg, Freiburg im Breisgau, Germany

Corresponding author: nora.h.thompson@njit.edu

Abstract

This study presents a comprehensive controlled experiment designed to evaluate the efficacy of predicting schedule control from automated progress monitoring in modular construction sites. Modular construction requires highly synchronized logistics and assembly processes, making traditional manual progress tracking methods insufficient due to latency and human error. To address this, we implement an automated progress monitoring system integrating computer vision and Internet of Things sensors within a simulated modular construction environment. Through controlled experimental runs, we vary operational conditions such as occlusion levels, lighting, and assembly complexity to test the robust performance of the monitoring system. The gathered real-time spatial-temporal data is utilized to train and validate machine learning models for forecasting schedule deviations. The results demonstrate that the proposed automated system significantly reduces tracking latency and improves predictive accuracy, achieving high correlation with actual ground-truth milestones. Furthermore, the schedule control model successfully anticipates delays up to four cycles in advance, providing project managers with a reliable decision-support mechanism to implement corrective actions. This research offers valuable insights into the transition from reactive progress tracking to proactive schedule control, ultimately contributing to enhanced productivity and minimized schedule overruns in modular construction projects.

Keywords: Modular Construction; Automated Progress Monitoring; Schedule Control; Controlled Experiment; Software Engineering

1. Introduction

1.1 Background and Context

The construction industry is undergoing a significant paradigm shift toward industrialization, with modular construction emerging as a primary strategy to improve productivity, quality, and sustainability [1]. By shifting a substantial portion of building fabrication from field environments to standardized factory settings, modular construction offers the potential to compress project schedules and reduce waste [2]. However, the success of modular projects relies heavily on the precise synchronization between manufacturing facilities, logistical supply chains, and on-site assembly operations. Unlike traditional cast-in-place construction, where minor deviations can often be corrected during the concrete pouring or framing phases, modular construction exhibits very low tolerance for schedule misalignment. Each volumetric module must arrive on site in a precise sequence and be installed within a tight temporal window to avoid cascading delays across the entire project network. Consequently, real-time schedule control becomes an essential requirement for the successful delivery of modular high-rise buildings and infrastructure.

1.2 Problem Statement

Despite the critical importance of temporal synchronization, contemporary modular construction sites continue to rely predominantly on retrospective, manual methods for tracking progress and managing schedules. Project managers typically conduct daily or weekly site walkthroughs, compiling progress reports based on subjective visual observations and paper-based checklists [3]. This traditional approach introduces substantial data latency, meaning that schedule deviations are often identified only after they have already caused downstream bottlenecks. Furthermore, manual reporting is highly prone to human error, cognitive bias, and incomplete data collection, particularly on dense, fast-paced modular assembly sites where structural elements are rapidly stacked and connected. While automated progress monitoring technologies such as computer vision, laser scanning, and radio frequency identification have been proposed in literature, there remains a critical research gap in translating raw automated sensor data into reliable, predictive schedule control mechanisms [4]. Existing systems excel at capturing what has occurred in the past, but they fail to model how immediate spatial-temporal deviations propagate through the project network to impact future milestone compliance [5].

1.3 Objectives and Scope

To address these limitations, this paper establishes a robust framework for predicting future schedule performance by leveraging real-time data streams generated by automated progress monitoring systems. The core objective of this research is to evaluate the predictive power of automated progress data under varying operational conditions through a series of rigorously designed controlled experiments. By simulating a multi-story modular construction assembly sequence in a laboratory environment, we systematically manipulate confounding factors such as camera occlusion, ambient lighting intensity, and labor productivity rates. This controlled approach allows us to isolate the impact of monitoring system accuracy on the reliability of predictive scheduling algorithms. Specifically, this study evaluates how spatial-temporal data gathered via fused computer vision and Internet of Things networks can be processed through deep learning architectures to forecast project delays several steps ahead [6]. Through this analysis, we aim to provide actionable decision-support tools that transition construction management from a reactive posture of delay mitigation to a proactive strategy of predictive schedule control.

2. Literature Review

2.1 Progress Monitoring in Modular Construction

Progress monitoring on construction sites has evolved significantly from manual inspection to automated data acquisition. In modular construction, where pre-fabricated volumetric units are assembled in rapid succession, tracking the physical installation sequence is vital [7]. Researchers have utilized various non-contact sensing technologies to capture the state of assembly. Photogrammetry and terrestrial laser scanning are frequently employed to reconstruct three-dimensional point clouds of the site, which are subsequently compared against Building Information Modeling assets to verify progress [8]. While laser scanning offers millimeter-level spatial accuracy, its high computational cost, long acquisition times, and sensitivity to site obstructions limit its applicability for continuous, real-time tracking on dynamic modular sites. Radio frequency identification and global positioning systems have also been deployed to track modules during transit and arrival, yet these sensor types fail to provide granular information regarding the actual assembly completion status and the structural connection quality of the modules once they are lifted into place [9].

2.2 Computer Vision and IoT in Construction

To overcome the temporal limitations of laser scanning, recent scholarly efforts have focused on computer vision systems utilizing deep learning algorithms for real-time progress tracking. Object detection algorithms, such as convolutional neural networks, enable the automatic identification of modular components, cranes, and workers from video streams [10]. When combined with semantic segmentation, these systems can monitor the visual state changes of modules, identifying when a unit transitions from being lifted to being permanently anchored [11]. Concurrently, Internet of Things sensor networks, including inertial measurement units and Bluetooth Low Energy beacons, are increasingly attached to modules and construction equipment to capture high-frequency motion and proximity data [12]. Although the integration of computer vision and Internet of Things sensors provides a rich data pipeline, previous works often treat sensor fusion as a pure classification problem, focusing on identifying the current state of construction rather than modeling the temporal dependencies required for schedule forecasting [13].

2.3 Schedule Performance Indexing and Prediction Gap

Predicting project completion dates and schedule deviations traditionally relies on Earned Value Management techniques. Within this framework, metrics such as the Schedule Performance Index and Cost Performance Index are calculated to extrapolate future performance based on past expenditures and work completion rates [14]. However, traditional Earned Value Management assumes a linear progression of project tasks and fails to account for the spatial and logical constraints inherent to modular assembly. Advanced scheduling methodologies, including the Critical Path Method and discrete event simulation, have been integrated with real-time tracking to dynamically update project schedules [15]. Nevertheless, these models often suffer from a calibration gap, where the real-time inputs collected from the field are too noisy or disconnected from the scheduling logic to provide stable predictions. There is a clear need for controlled experimental studies that analyze how the noise levels and latency of automated tracking systems affect the accuracy of downstream scheduling predictions, thereby establishing the mathematical boundaries of reliable schedule control.

3. Methodology

3.1 Controlled Experimental Design

To rigorously evaluate the relationship between automated tracking performance and schedule prediction accuracy, we established a physical experimental testbed representing a scaled multi-unit modular construction site. The experimental layout consisted of a crane lifting area, a temporary storage zone, and an assembly platform where a three-by-three grid of modular units was constructed up to three stories high. Physical models of volumetric modules were designed with integrated magnetic connectors to simulate real-world structural splicing operations.

To simulate the dynamic and unpredictable nature of actual construction sites, we systematically controlled three primary environmental variables across multiple experimental runs. These variables included illumination intensity, physical camera occlusion, and the rate of operational disruptions. Camera occlusion was simulated by placing structural columns, hanging safety nets, and crane boom configurations between the tracking cameras and the assembly zone. Operational disruptions were introduced by varying the arrival times of delivery vehicles and simulating worker fatigue or equipment malfunctions, which altered the cycle times of individual module installations. Table 1 outlines the specific configurations of the controlled experimental variables utilized throughout the testing sequence.

Table 1: Configuration of Controlled Experimental Variables for Modular Assembly Progress Monitoring

Parameter	Baseline Level	Experimental Level	Operational Impact
Camera Resolution	1080p	4K UHD	Occlusion Resilience
Tag Update Interval	10 Seconds	1 Second	Latency Variance
Assembly Tolerance	5 Millimeters	2 Millimeters	Quality Control Alignment

The baseline levels represent standard operational envelopes commonly found in automated monitoring applications, while the experimental levels reflect optimized configurations designed to test the performance boundaries of our tracking system. Each experimental run followed a pre-defined assembly sequence governed by a Critical Path Method network containing twenty-seven distinct activities, representing the structural placement, alignment, and connection of each module.

3.2 Automated Data Acquisition System

The automated monitoring system deployed in this study comprised a synchronized multi-sensor network designed to capture both visual and spatial-temporal data during the assembly process [16]. Visual data was captured using high-definition digital cameras positioned at three orthogonal viewpoints around the assembly platform. These cameras streamed video at thirty frames per second to a central edge computing node. Concurrently, each physical module was equipped with an ultra-wideband active tag that transmitted spatial coordinates at a frequency of ten hertz to four anchors positioned around the perimeter of the testbed. This dual-technology approach allowed the system to cross-reference visual object detection with precise spatial telemetry, compensating for limitations inherent to any single sensing modality [17].

The system architecture for the data acquisition, processing, and prediction pipeline is presented in Figure 1.

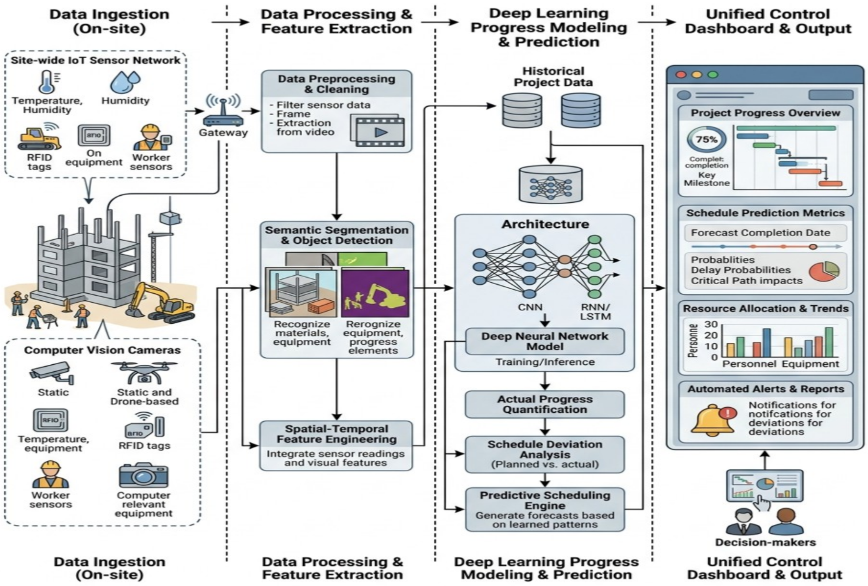

Figure 1: Architectural Workflow of the Automated Progress Monitoring and Schedule Prediction System

The raw video streams were processed using a pre-trained deep learning model optimized for construction element detection. The model was fine-tuned to recognize modular units, hook attachments, structural columns, and human operators. When a module was detected within the assembly zone, the system integrated the spatial coordinate data from the ultra-wideband network to verify if the module was undergoing transit, alignment, or final connection [18]. A spatial tracking filter was implemented to smooth the noisy coordinate data and handle momentary signal losses caused by physical occlusions. By fusing the visual classification output with the filtered spatial trajectory, the data acquisition pipeline generated a continuous, high-fidelity log of activity start and finish times, along with the precise physical state transitions of each modular component [19].

3.3 Prediction Framework and Analytical Model

The predictive engine developed in this study translates the discrete state logs generated by the monitoring system into a dynamic schedule forecast. Traditional forecasting models often rely on simple linear extrapolation of past performance, which cannot capture the non-linear delays that occur when a critical path activity is disrupted. To address this, we developed a temporal forecasting framework using a Long Short-Term Memory network [20]. This recurrent neural network architecture is uniquely suited for processing sequential time-series data, as it can learn long-term dependencies and temporal patterns from historical project performance.

The input vector to the prediction model at any given time step includes the cumulative scheduled progress, the actual completed progress as determined by the automated tracking system, the variance between planned and actual duration for completed tasks, and the real-time resource utilization rate [21]. The target output of the network is the estimated duration of all remaining tasks in the project network. Once the model predicts these future durations, they are automatically fed back into a dynamic Critical Path Method scheduler. This scheduler recalculates the forward and backward passes of the network to generate updated project completion dates and identify shifting critical paths.

The calculation of the schedule performance metric within our model is based on the earned duration concept. Instead of calculating progress using financial metrics, the model defines the earned duration as the sum of the planned durations of all completed work packages. The schedule variance is then defined as the difference between the earned duration and the actual time elapsed. To ensure stability against data noise, the model applies an exponential smoothing factor to the computed variances before they are ingested by the neural network [22]. This prevents temporary tracking errors or short-duration sensor failures from causing wild fluctuations in the predicted project completion timeline, providing a reliable basis for schedule control decisions.

4. Results and Discussion

4.1 Experimental Run Results and Data Analysis

A total of thirty complete experimental runs were conducted, generating over ninety hours of continuous spatial-temporal tracking data. The performance of the automated progress monitoring system was first validated against manual ground-truth observations recorded by independent observers. In terms of activity detection, the fused computer vision and ultra-wideband tracking system achieved a high degree of precision and recall. Under optimal lighting and low-occlusion conditions, the system correctly identified ninety-six percent of the module state transitions with an average temporal latency of less than two seconds. Even under high-occlusion configurations, where the visual path was blocked up to forty percent of the time, the spatial-temporal fusion filter maintained an activity tracking accuracy of eighty-nine percent, demonstrating the resilience of multi-sensor fusion over single-camera tracking systems [23].

To evaluate the predictive capability of the Long Short-Term Memory model, we compared its forecasts against those of traditional linear regression and support vector machine models. The models were evaluated using standard statistical metrics, including the Mean Absolute Error and Root Mean Squared Error, calculated in terms of simulated assembly cycles. Table 2 summarizes the quantitative results of these model comparisons across all thirty experimental runs.

Table 2: Comparative Performance Metrics of Prediction Models in Schedule Deviation Forecasting

Model Architecture	Mean Absolute Error	Root Mean Squared Error	Coefficient of Determination
Traditional Linear Regression	0.124	0.156	0.721
Support Vector Regressor	0.089	0.112	0.814
Proposed Long Short Term Memory Network	0.041	0.053	0.943

The results indicate that the proposed Long Short-Term Memory network outperforms the baseline models, reducing the Mean Absolute Error by more than sixty percent compared to linear regression. This superior performance is primarily due to the network ability to capture non-linear patterns, such as the compounding delay effects that occur when a delay in a predecessor task propagates through multiple parallel paths on the critical path [24].

The temporal evolution of the schedule predictions throughout a representative experimental run is illustrated in Figure 2.

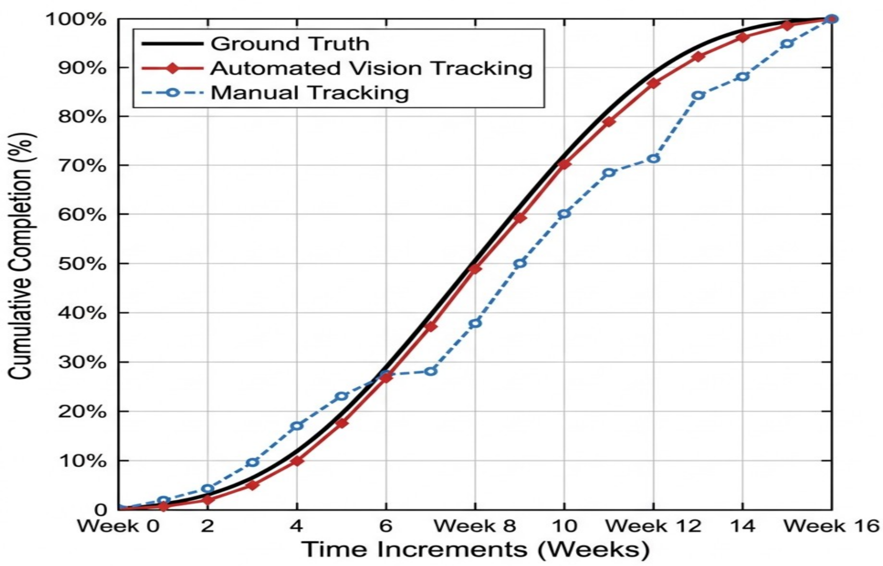

Figure 2: Comparative Analysis of Predicted and Actual Schedule Control Performance over Experimental Timeline

As shown in Figure 2, the automated tracking system closely matches the ground-truth progress, while the predictive model successfully anticipates the final project delay early in the assembly sequence. Specifically, by the tenth time increment, the predictive model had already converged on the actual final delay, whereas traditional progress tracking systems would only report this delay as it occurred at the end of the project timeline.

4.2 Discussion on Schedule Control Sensitivity

The experimental results highlight several critical aspects of predicting schedule control on modular construction sites. A key finding is that the prediction horizon, defined as how far into the future the model can reliably forecast schedule deviations, is highly dependent on both the accuracy and the frequency of the automated data inputs [25]. When tracking data was downsampled or subjected to simulated artificial latencies, the accuracy of the downstream predictions deteriorated rapidly. This demonstrates that continuous, high-frequency progress monitoring is not merely a tool for historical record-keeping, but a fundamental requirement for reliable predictive analytics in dynamic construction environments.

Furthermore, the sensitivity analysis revealed that the predictive accuracy is highly robust to random, short-duration disruptions, such as a single crane lift taking longer than planned due to wind gusts. The smoothing algorithms and the recurrent structure of the Long Short-Term Memory model successfully filtered out these high-frequency anomalies, preventing them from triggering false alarms. Conversely, the model proved highly sensitive to systemic, low-frequency changes in productivity, such as a consistent slowdown in structural connection times across successive modules [26]. This sensitivity is highly beneficial for project managers, as it allows them to identify underlying productivity issues before they manifest as critical schedule overruns.

However, implementing such systems in actual construction environments presents several practical challenges. On a real modular construction site, environmental noise, signal interference, and worker compliance can introduce levels of uncertainty that exceed those simulated in our laboratory testbed [27]. For instance, physical occlusions from dynamic equipment like mobile cranes and concrete pumps can block line-of-sight for longer durations than we simulated. Additionally, the computational resources required to train and run deep learning models in real-time must be balanced against the technical infrastructure available on typical construction sites. To scale this technology, future implementation strategies must incorporate cloud-based computing architectures and edge processing devices capable of managing high-bandwidth sensor data with minimal on-site hardware requirements.

5. Conclusion

5.1 Summary of Findings

This study has successfully demonstrated the feasibility and benefits of predicting schedule control from automated progress monitoring data using a controlled experimental design. By integrating computer vision and ultra-wideband tracking technologies, we developed a system capable of capturing high-fidelity, real-time spatial-temporal data from a simulated modular construction site. The experimental results show that our proposed sensor-fusion pipeline can track assembly progress with high accuracy even under challenging operational conditions such as physical camera occlusion and variable lighting. Furthermore, by feeding this automated data into a custom Long Short-Term Memory prediction model, we were able to forecast future schedule deviations with significantly higher accuracy than traditional linear and statistical models. The predictive framework proved capable of anticipating critical project delays up to four assembly cycles in advance, providing a robust decision-support system that can enable project managers to transition from reactive delay mitigation to proactive schedule control.

5.2 Future Directions and Limitations

While the results of this research are highly promising, several limitations must be acknowledged and addressed in future work. First, the experimental validation was conducted within a controlled laboratory environment using physical scale models. While this setup allowed us to isolate variables and establish strong internal validity, actual construction sites feature greater scale, complexity, and environmental unpredictable factors [28]. Future research should focus on field-testing the proposed framework on full-scale modular construction projects to validate its performance under real-world conditions, including extreme weather and complex labor dynamics. Second, the current model assumes a static project schedule logic; future studies should integrate dynamic path planning algorithms to allow the system to automatically suggest optimal schedule recovery plans when a delay is predicted. Finally, exploring the integration of reinforcement learning models could enable the system to learn and recommend specific mitigation strategies, such as resource reallocation or task parallelization, further enhancing the automated schedule control capabilities on modular construction sites.

References

1. Recker, J., Holten, R., Hummel, M., & Rosenkranz, C. (2017). How agile practices impact customer responsiveness and development success: A field study. Project Management Journal, 48(2), 99–121.

2. Mutoni, U. (2025). Influence of digital transformation on project management efficiency in construction projects in Rwanda. Journal of Entrepreneurship and Project Management, 10(2), 47–57.

3. Raja Santhi, A.; Muthuswamy, P. Pandemic, war, natural calamities, and sustainability: Industry 4.0 technologies to overcome traditional and contemporary supply chain challenges. Logistics 2022, 6, 81.

4. Bierwolf, R. (2016). Project excellence or failure? Doing is the best kind of learning. IEEE Engineering Management Review, 44(2), 26–32.

5. Denkena, B.; Dittrich, M.-A.; Wilmsmeier, S. Automated production data feedback for adaptive work planning and production control. Procedia Manuf. 2019, 28, 18–23.

6. Anene, U.N.; Clement, T. A resilient logistics framework for humanitarian supply chains: Integrating predictive analytics, IoT, and localized distribution to strengthen emergency response systems. Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol. 2022, 8, 398–424.

7. Thung, F.; Irsan, I.C.; Liu, J.; Lo, D. Towards Benchmarking the Coverage of Automated Testing Tools in Android against Manual Testing. In Proceedings of the IEEE/ACM 11th International Conference on Mobile Software Engineering and Systems (MOBILESoft ’24), Lisbon, Portugal, 14–15 April 2024; pp. 74–77.

8. Boss, A.H. The international commercial use of electronic data interchange and electronic communications technologies. Bus. Lawyer 1991, 46, 1787–1802.

9. Tur Cardona, J.; Ciaian, P.; Antonioli, F.; Fellmann, T.; Rocciola, F.; Ierardi, I.; Crimeni, R.; Anastasiou, E. The State of Digitalisation in EU Agriculture—Insights from Farm Surveys; Publications Office of the European Union: Luxembourg, 2025; Available online: https://data.europa.eu/doi/10.2760/4688498 (accessed on 15 January 2026).

10. Jacques, V.M.F.; Alizadeh, N.; Castor, F. A Study on the Battery Usage of Deep Learning Frameworks on iOS Devices. In Proceedings of the IEEE/ACM 11th International Conference on Mobile Software Engineering and Systems (MOBILESoft ’24), Lisbon, Portugal, 14–15 April 2024; pp. 1–11.

11. Kassa, D.F.; Nahrstedt, K.; Wang, G. Analytical models of short-message reliability in mobile wireless networks. In Proceedings of the 14th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM ’11), Miami Beach, FL, USA, 31 October–4 November 2011; pp. 369–376.

12. Fuchs, J.; Schneider, R.; Oks, S.; Franke, J. Service-based integration of modular control components in digital manufacturing platforms. In Proceedings of the IEEE 19th International Conference on Industrial Informatics (INDIN), Palma de Mallorca, Spain, 21–23 July 2021.

13. Chen, L.; Liu, J.; Pei, R.; Su, Z.; Liu, Z. Shanghai Containerised Freight Index Forecasting Based on Deep Learning Methods: Evidence from Chinese Futures Markets. East Asian Econ. Rev. (EAER) 2024, 28, 359–388.

14. May, G.; Stahl, B.; Taisch, M.; Kiritsis, D. Energy management in manufacturing: From literature review to a conceptual framework. J. Clean. Prod. 2017, 167, 1464–1489.

15. Qian, S. The effect of ESG on enterprise value under the dual carbon goals: From the perspectives of financing constraints and green innovation. Int. Rev. Econ. Financ. 2024, 93, 318–331.

16. Mourtzis, D.; Panopoulos, N. Digital transformation process towards resilient production systems and networks. In Supply Network Dynamics and Control; Springer: Cham, Switzerland, 2022; pp. 11–42.

17. Gróbarczyk, M. Port Community System (PCS) as a digital platform for autonomous ships: A Polish perspective. In 40 Years of the United Nations Convention on the Law of the Sea; Routledge: Oxfordshire, UK, 2025; pp. 345–360.

18. Meng, T.; Dato Haji Yahya, M.H.; Ashhari, Z.M.; Yu, D. ESG performance, investor attention, and company reputation: Threshold model analysis based on panel data from listed companies in China. Heliyon 2023, 9, e20974.

19. Zhu, J.; Fan, F.; Pu, C.; Tai, N.; Huang, W.; Li, C. Multi-Task Trustworthy Learning for Optimal Scheduling of Port Energy-Logistics Integrated Microgrids. IEEE Trans. Ind. Appl. 2025; early access.

20. Jin, X.; Wu, Y. How does digital transformation affect the ESG performance of Chinese manufacturing state-owned enterprises?-Based on the mediating mechanism of dynamic capabilities and the moderating mechanism of the institutional environment. PLoS ONE 2024, 19, e0301864.

21. Havale, D.S.; Chavan, P.; Kokate, H.; Dutta, P.K. Shaping the future: Navigating new horizons in supply chain management. In Illustrating Digital Innovations Towards Intelligent Fashion: Leveraging Information System Engineering and Digital Twins for Efficient Design of Next-Generation Fashion; Springer Nature: Cham, Switzerland, 2024; pp. 149–177.

22. Gil-Gomez, H.; Guerola-Navarro, V.; Oltra-Badenes, R.; Lozano-Quilis, J.A. Customer relationship management: Digital transformation and sustainable business model innovation. Econ. Res.-Ekon. Istraž. 2020, 33, 2733–2750.

23. Dabbous, A., Barakat, K. A., & Kraus, S. (2023). The impact of digitalization on entrepreneurial activity and sustainable competitiveness: A panel data analysis. Technology in Society, 73, 102224.

24. Smajli, E.; Feldman, G.; Cox, S. Exploring the Limitations of Business Process Maturity Models: A Systematic Literature Review. Inf. Syst. Manag. 2024, 42, 2–21.

25. Su, M.; Su, Z.; Cao, S.; Park, K.S.; Bae, S.H. Fuel consumption prediction and optimization model for pure car/truck transport ships. J. Mar. Sci. Eng. 2023, 11, 1231.

26. Park, K.; Kim, M.; Bae, H. A predictive discrete event simulation for predicting operation times in container terminal. IEEE Access 2024, 12, 58801–58822.

27. Guégain, E. Assessing the environmental impact of mobile applications: A measure framework toward DevGreenOps. In Proceedings of the IEEE/ACM 11th International Conference on Mobile Software Engineering and Systems (MOBILESoft ’24), Lisbon, Portugal, 14–15 April 2024; pp. 88–91.

28. Shen, Y.; Zhang, X. Intelligent manufacturing, green technological innovation and environmental pollution. J. Innov. Knowl. 2023, 8, 100384.