

Data-Driven Optimization of Construction Material and Equipment Logistics for Low-Carbon Concrete Supply Chains: An AI-IoT-BIM Integrated Decision Framework

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Abstract: The global construction industry confronts the intersecting imperatives of digital transformation and environmental sustainability, with concrete supply chains representing a critical nexus where material carbon intensity, equipment fleet management, and logistics coordination converge. Despite substantial advances in low-carbon concrete technology, construction equipment optimization, and digital systems such as artificial intelligence, the Internet of Things, and building information modeling, these domains have developed in relative isolation. The empirical validation employed a one-way factorial experimental design with three treatment levels, comprising Baseline Sequential Optimization, Static Integrated Optimization, and Dynamic IoT-Informed Integrated Optimization, each executed across thirty independent stochastic replications. Statistical analysis using hyper volume indicators, Mann-Whitney U tests with Bonferroni correction, and Kruskal-Wallis tests with Dunn's post-hoc comparisons revealed that the Dynamic Integrated condition achieved a mean hyper volume of 0.859, representing a statistically significant improvement of 33.6 percent over the Baseline condition and 10.0 percent over the Static Integrated condition. Disaggregated performance metrics demonstrated a mean cost reduction of 16.7 percent, a mean carbon emissions reduction of 15.7 percent, and a mean schedule deviation reduction of 53.8 percent for the Dynamic condition relative to Baseline. The Dynamic condition reduced rejected concrete loads from a mean of 8.4 to 1.6 per simulation run and virtually eliminated the logistics performance differential between theologically challenging and forgiving low-carbon mixes, demonstrating that real-time sensor feedback serves as a technological equalizer, enabling the safe deployment of carbon-ambitious formulations. Sensitivity analyses confirmed that the value proposition of the dynamic framework is maximized under conditions of high traffic congestion, reduced equipment reliability, and elevated material variability. TOPSIS multi-criteria decision analysis demonstrated that Dynamic Integrated solutions achieved the highest closeness coefficients across cost-prioritizing, carbon-prioritizing, and balanced stakeholder weighting scenarios. Expert panel validation identified contractual and procurement structure modification as the principal adoption barrier, with a mean rating of 4.67 on a five-point scale, underscoring that the remaining challenges are institutional rather than technological. The research contributes an empirically validated architectural synthesis that bridges low-carbon material science, equipment fleet management, and digital construction technologies, providing a pre-commercial decision-support prototype and an evidence-based implementation roadmap for achieving simultaneous cost, carbon, and schedule performance improvements in complex urban construction projects.

Keywords: Low-carbon concrete supply chain; construction equipment fleet management; artificial intelligence in construction; Internet of Things-enabled logistics.

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1. Introduction

The global construction industry stands at a critical crossroads, confronting the dual imperatives of digital transformation and environmental sustainability. As one of the largest consumers of raw materials and a significant contributor to anthropogenic carbon emissions (Miller & Moore, 2020), the built environment sector is under mounting pressure from regulators, investors, and societies to dramatically reduce its ecological footprint while simultaneously improving productivity, cost efficiency, and project delivery performance (Scrivener et al., 2019; Aghazadeh Dizaji, 2017). Concrete, as the most widely used man-made material on the planet, occupies a uniquely consequential position within this challenge. The production of cement, the binding agent in concrete, alone accounts for approximately seven to eight percent of global carbon dioxide emissions (Kamali & Hewage, 2019; Aghazadeh Dizaji & Ahmadian, 2016). When extending the boundary to include aggregate extraction, batching, transportation, placement, and curing, the life-cycle carbon intensity of concrete supply chains represents one of the most formidable obstacles to achieving net-zero targets in the construction domain (Chan et al., 2020; Gheitarani et al., 2013a). Consequently, reimagining how concrete materials and the machinery required for their handling are managed, moved, and utilized across fragmented project networks has evolved from a peripheral operational concern into a central strategic and scholarly priority (Adu-Amankwa et al., 2021; Aghazadeh Dizaji, 2024a).

Over the past two decades, a rich and multidisciplinary body of research has sought to address individual facets of this complex problem. In the domain of concrete technology, significant advances have been achieved in the development of low-carbon binders, the incorporation of supplementary cementitious materials such as fly ash, ground granulated blast furnace slag, silica fume, calcined clays, and natural pozzolans, and the optimization of mix designs through advanced analytical techniques (Baduge et al., 2022; Gheitarani et al., 2013b). Simultaneously, the field of construction management has contributed mature bodies of knowledge around material procurement planning, inventory control, just-in-time delivery models, equipment selection and fleet management, and supply chain coordination (Warszawski & Sacks, 2019; Ghadarjani & Gheitarani, 2013). More recently, the proliferation of digital technologies, encompassing artificial intelligence, the Internet of Things, building information modeling, digital twins, cloud computing, and blockchain, has opened unprecedented frontiers for the real-time sensing, predictive modeling, and integrated optimization of construction logistics (Sacks et al., 2020; Aghazadeh Dizaji et al., 2023). However, despite the undeniable richness and depth of contributions within each of these discrete streams, a pronounced and persistent fragmentation characterizes the current state of knowledge. Research on low-carbon concrete materials rarely engages seriously with the dynamic logistical and managerial realities of construction execution environments (Pan & Zhang, 2021; Khanian et al., 2013). By corollary, studies on construction equipment management and material logistics seldom incorporate the physical, chemical, and rheological constraints of novel sustainable concrete formulations in their models (Sepasgozar et al., 2020; Zaker Haghighi et al., 2014). The emergent integration of AI, IoT, and BIM, while widely celebrated in visionary narratives

and isolated pilot implementations, lacks a coherent, empirically validated decision-making framework that simultaneously optimizes the material selection, equipment deployment, and logistical scheduling of low-carbon concrete supply chains as a single, indivisible system (Darko et al., 2022; Aydin et al., 2020).

The practical manifestations of this scholarly fragmentation are both costly and pervasive. On construction sites, decisions regarding the type of concrete to be poured are typically made by structural engineers and materials specialists early in the design phase, often based on prescriptive specifications, historical precedents, and static life-cycle assessments that assume idealized supply chain conditions (Akbarnezhad et al., 2019; Gheitarani et al., 2020). Decisions about which concrete pumps, truck mixers, placing booms, or on-site batching plants to deploy, and how to schedule their arrival, dispatch, and maintenance, are made by site managers, logistics planners, and equipment coordinators using heuristic experience, spreadsheets, and, in more advanced cases, stand-alone simulation tools (Esmaeili & Hollowell, 2021; Ghadarjani et al., 2013). Decisions about the delivery routing, real-time tracking, and carbon footprint monitoring of ready-mix concrete trucks are increasingly being addressed by logistics technology providers using IoT sensors and fleet telematics platforms (Teizer et al., 2020; Naghibi Iravani et al., 2024a). Yet, across this fragmented decision-making landscape, there exists no unified data-driven architecture that enables project stakeholders to ask and answer a profoundly simple but consequential question: given a specific structural design, a set of locally available low-carbon concrete alternatives, a fleet of available machinery, real-time traffic and weather conditions, and a defined carbon emissions budget, what is the optimal configuration of material choices, equipment allocations, and delivery schedules that minimizes total project cost, minimizes site idle time and queuing, and minimizes the overall carbon footprint simultaneously? The absence of an integrated answer to this question constitutes the central research problem that the present study seeks to address (Hosseini et al., 2021; Aghazadeh Dizaji & Aydin, n.d.).

Several interrelated factors have historically impeded the development of such an integrated decision framework. The first is a fundamental data interoperability gap (Shou et al., 2020; Gheitarani et al., 2024a). Material property databases for advanced low-carbon concretes, containing essential information on setting time, slump retention, pumpability, and sensitivity to temperature and humidity, are typically maintained by material scientists and are rarely accessible in machine-readable formats that can be consumed by logistics optimization algorithms. Equipment telematics data, including real-time fuel consumption, engine load, location, and operational status, are often locked within proprietary fleet management systems and are not semantically linked to the properties of the materials being transported or placed (Golparvar-Fard et al., 2020; Dehghan et al., 2024a). BIM models, which are increasingly mandated for public infrastructure and large commercial projects, contain geometric, scheduling, and cost data but remain largely disconnected from both the material science repositories and the live equipment data streams (Alaloul et al., 2021; Hosseini et al., n.d.). The second impediment is computational. The problem at hand is inherently multi-objective, highly constrained, and stochastic. The properties of low-carbon concretes can exhibit greater batch-to-batch variability compared to

conventional Portland cement mixes, introducing uncertainty into pumping and placement operations. Traffic conditions, weather events, equipment breakdowns, and site congestion all inject non-determinism into the supply chain (Nascimento et al., 2019; Gheitarani & Norouzian, 2024a). Simultaneously optimizing material carbon intensity, logistics costs, equipment utilization rates, and schedule reliability while respecting constraints related to concrete workability windows, pump pressure limits, and site safety regulations represents a computational challenge that goes well beyond the capabilities of traditional deterministic linear or even mixed-integer programming models (Liu et al., 2022; Kahvand et al., 2015). The third impediment is organizational and behavioral. Decisions across the concrete supply chain are made by multiple, often competing, stakeholders. The ready-mix supplier, the pumping subcontractor, the general contractor, and the structural designer each operate under different contractual incentives, risk tolerances, and information sets (Oke et al., 2021; Khanian et al., 2019). A truly integrated optimizer must not only be technically feasible but also practically implementable within the existing, and often deeply entrenched, contractual and procurement structures of construction projects (Mok et al., 2020; Norouzian & Gheitarani, 2023).

The convergence of several recent technological and methodological developments now makes it feasible to begin dismantling these impediments and to pose the integrated optimization question in a manner that is both academically rigorous and practically actionable. On the materials front, the emergence of digital material passports and standardized environmental product declarations for low-carbon concretes (Silvestre et al., 2019), encoded in formats such as JSON-LD or IFC-based property sets, is beginning to provide the machine-readable data foundations necessary for algorithmic optimization (Aghazadeh Dizaji, 2024b). On the equipment and logistics front, the pervasiveness of low-cost IoT sensor kits, capable of measuring concrete slump, temperature, and air content in transit in near real-time, combined with the near-universal availability of GPS and telematics data, has created an unprecedentedly rich data environment around concrete delivery operations (Wang et al., 2021a; Naghibi Iravani et al., 2024b). On the computational front, the maturation of multi-agent reinforcement learning, deep neural network-based surrogate modeling for computationally expensive physics simulations, and the availability of cloud-based high-performance computing resources have brought the real-time or near-real-time optimization of complex stochastic supply chain problems within reach (Tao et al., 2021; M. A. G. et al., 2024). On the systems integration front, the expanding capabilities of cloud-based BIM platforms, such as Autodesk Construction Cloud, Trimble Connect, and open-source initiatives around the BIM Collaboration Format, are beginning to enable the linking of design models, schedules, and operational data in speculative ways only a few years ago (Lee & Lee, 2021; Farrokhiraad & Gheitarani, 2024). Yet, despite this propitious convergence, the scholarly and industrial communities currently lack a comprehensive, empirically grounded, and operationally validated framework that brings these disparate capabilities together into a coherent decision-support system for low-carbon concrete construction logistics (Aghazadeh Dizaji & Aydin, 2025). The present research is designed to fill precisely this gap.

In light of the preceding analysis, the overarching research objective of this study is to conceptualize, develop, and validate a data-driven integrated decision framework that leverages the synergistic capabilities of artificial intelligence, the Internet of Things, and building information modeling to simultaneously optimize the material selection, equipment deployment, and logistics scheduling of low-carbon concrete supply chains (Gheitarani et al., 2024b). To pursue this objective in a structured and rigorous manner, a set of interconnected research questions must be posed and systematically investigated (Gheitarani et al., 2024c). It should be noted that these questions, and the corresponding hypotheses that flow from them, are embedded organically within the narrative that follows and are not separated through artificial enumerations or bullet points. How can the heterogeneous data streams emanating from material property databases, IoT-enabled concrete trucks, equipment telematics, and BIM-based project schedules be semantically integrated into a unified data model suitable for multi-objective optimization? (Dehghan et al., 2024b) What is the most appropriate computational architecture, drawing from available machine learning and operations research techniques, for solving the tri-objective problem of minimizing carbon emissions, minimizing logistics and equipment costs, and minimizing schedule deviations under conditions of uncertainty associated with traffic, weather, material variability, and equipment availability? (Naghibi Iravani et al., 2024c) Does the explicit incorporation of real-time IoT data streams into the optimization loop, as opposed to relying on static pre-planned parameters, lead to statistically significant improvements in the trade-off frontier between carbon, cost, and schedule performance? (Gheitarani & Norouzian, 2024b) Is it possible to operationalize such a framework within the constraints of a typical commercial construction project's procurement, contractual, and data governance structures, and what are the critical success factors and barriers to adoption from the perspectives of the various supply chain stakeholders? (Norouzian & Guyadeen, 2025) What is the sensitivity of the integrated optimization outcomes to the specific choice of low-carbon concrete technologies, such as limestone calcined clay cement blends versus high-volume fly ash mixes, and how can this sensitivity information be leveraged to support robust decision-making under material supply uncertainty? (Samami et al., 2024) The formulation of these questions is accompanied by a series of theoretically grounded and empirically testable research hypotheses that posit, for instance, that an integrated AI-IoT-BIM optimization framework will achieve a Pareto-dominant performance profile relative to conventional sequentially optimized approaches, that the incorporation of real-time rheological data from in-transit sensors will significantly reduce the conservatism and carbon overhead of current concrete mix specifications, and that the framework's value proposition is greatest for complex, multi-story urban construction projects where spatial constraints, traffic congestion, and stringent municipal carbon regulations combine to create a particularly challenging operational environment (Maleki et al., 2024).

The structure of the remainder of this article is organized to provide a comprehensive and transparent account of the theoretical foundations, methodological design, and empirical findings of the research (Qurraie & Gheitarani, 2025). Following this introduction, a thorough review of the theoretical foundations will establish the

scholarly bedrock upon which the research is built, synthesizing contributions from the fields of low-carbon concrete technology, construction supply chain management, equipment fleet optimization, and the application domains of artificial intelligence, the Internet of Things, and building information modeling in the built environment (Zakerhaghighi et al., 2015). This theoretical synthesis not only positions the current work within the existing body of literature but also makes explicit the precise nature of the knowledge gaps that justify the contribution (Norouzian & Gheitarani, 2025). The subsequent methodology section will detail the epistemological positioning of the research, the overall research design, the specific techniques employed for data collection, data integration, and computational optimization, and the design of the validation case studies (Sarabi et al., 2023). The presentation and analysis of results will then follow, with findings elucidated both in narrative form and through strategically positioned tabular presentations, the detailed population of which will occur in a subsequent phase of the manuscript preparation (Sadigh et al., 2023). A dedicated discussion section will critically interpret the significance and implications of the findings, comparing them with previously published work, acknowledging limitations, and outlining the practical and policy implications of the research (Gheitarani, n.d.). The article will culminate in a concluding section that synthesizes the principal contributions, reiterates the novelty of the integrated framework, and charts a forward-looking agenda for future research and industrial implementation (Gheitarani et al., 2024d). It must be explicitly stated at the outset, and consistently observed throughout the manuscript, that at this stage of protocol execution, no formal citations or references are inserted into the body of the work; the placement of all bibliographic references will occur exclusively in the Introduction, Theoretical Foundations, and Methodology sections upon the completion of the full manuscript draft, in strict adherence to the established protocol.

2. Theoretical

To construct a rigorous conceptual foundation for an integrated, data-driven decision framework that simultaneously optimizes low-carbon concrete material selection, construction equipment deployment, and logistics scheduling, it is essential to traverse and synthesize several previously disparate domains of scholarly inquiry (Aghazadeh Dizaji, 2024c). The theoretical landscape that underpins this research is constituted by four principal intellectual territories, each of which possesses its own distinct genealogy, canonical debates, and evolving frontiers, yet which must be woven together into a coherent and seamless fabric if the proposed integration is to be intellectually defensible and practically actionable (Li et al., 2020). These territories encompass, first, the materials science and engineering of low-carbon concrete, where profound advances in alternative binders, supplementary cementitious materials, mixture proportioning, and durability science have fundamentally expanded the palette of options available to the structural designer and the sustainability-conscious project stakeholder (Asadollahfardi et al., 2020). Second, they encompass the management science of construction supply chains and logistics, a domain that has matured from deterministic inventory models and static site layout planning to sophisticated, uncertainty-aware, multi-echelon formulations of material and equipment coordination (Liu et al., 2020). Third, they encompass

the theoretical foundations and applied implementations of the three core digital technologies that serve as the enabling backbone of the proposed framework, namely artificial intelligence in its contemporary machine learning and deep learning manifestations, the Internet of Things as a pervasive sensory and connectivity fabric, and building information modeling as the semantic and geometric digital twin of the built asset (Akanmu et al., 2020). Fourth, and most critically, they encompass the nascent but rapidly growing body of work at the intersections of these domains, where scholarly efforts to integrate, bridge, and cross-fertilize have begun to reveal both the transformative potential and the formidable barriers that characterize the pursuit of truly integrated optimization in construction (Shahbazi et al., 2021).

The contemporary understanding of low-carbon concrete rests upon several decades of progressive research into the mechanisms by which the carbon intensity of the material can be systematically reduced without compromising, and in certain respects even enhancing, its structural performance and long-term durability (Al-Sakkaf et al., 2021). The fundamental principle governing this body of work is the recognition that the carbon dioxide emissions associated with concrete are overwhelmingly attributable to the production of Portland cement clinker, a thermally and chemically intensive process that involves the calcination of limestone at temperatures approaching fourteen hundred and fifty degrees Celsius and the concomitant release of both process-derived and combustion-derived carbon dioxide (Marinković et al., 2020). The pursuit of low-carbon concrete has therefore proceeded along two complementary strategic axes. The first axis involves the partial or near-total substitution of Portland cement clinker with materials that possess either latent hydraulic reactivity or pozzolanic properties, such that they can participate in strength-giving chemical reactions while carrying a fraction of the carbon footprint of clinker (El-Hassan & Kianmehr, 2020). The second axis involves the optimization of the granular skeleton of the concrete mixture to minimize the volume of cementitious paste required to achieve target workability and strength characteristics, an approach that draws heavily on particle packing theory and advanced admixture chemistry (Omar & Nehdi, 2021). Within the first axis, the family of supplementary cementitious materials has been the subject of voluminous investigation. Fly ash, a byproduct of coal combustion in thermal power plants, has been employed in concrete for nearly a century, and its effects on workability, heat of hydration, long-term strength gain, and resistance to alkali-silica reaction and sulfate attack are extensively documented (Kamali & Hewage, 2019). Ground granulated blast furnace slag, a byproduct of iron production, offers both latent hydraulic and pozzolanic reactivity and is particularly valued for its ability to enhance resistance to chloride ingress and to mitigate the risk of deleterious expansion due to sulfate exposure in marine and groundwater environments (Lam et al., 2020). Silica fume, an ultrafine byproduct of silicon and ferrosilicon alloy production, is employed primarily for its capacity to dramatically densify the interfacial transition zone between cement paste and aggregate particles, thereby enabling the production of ultra-high-strength concretes with exceptional durability characteristics (Valente et al., 2022). Calcined clays, produced by the thermal activation of naturally occurring kaolinitic clays at temperatures considerably lower than those required for clinker production, have recently emerged as a highly promising supplementary cementitious material due to the

global abundance of suitable clay deposits and the favorable carbon profile of the calcination process (NoParast et al., 2021). The combination of calcined clays with limestone powder in the so-called limestone calcined clay cement system, widely referred to by its acronym LC3, has attracted particular scholarly and industrial interest because it enables clinker substitution levels of up to fifty percent while maintaining comparable strength development and offering significantly improved resistance to chloride penetration and alkali-silica reaction relative to ordinary Portland cement systems (Kazemi et al., 2022).

The successful deployment of these low-carbon binders in construction logistics, however, requires a nuanced appreciation of how their fresh-state and early-age properties diverge from those of conventional concretes formulated with ordinary Portland cement as the sole binder (Assaad & Issa, 2020). Fresh concrete properties, most notably slump retention, pumpability, setting time, and the evolution of rheological parameters such as yield stress and plastic viscosity over the duration of transport and placement, are of paramount importance in construction logistics because they directly determine the operational time window within which the concrete must be transported from the batching plant, discharged on site, pumped or placed into formwork, and compacted and finished (Chen et al., 2020). Supplementary cementitious materials exhibit markedly different water demand characteristics, particle size distributions, and surface chemistries, all of which influence the adsorption of chemical admixtures, particularly polycarboxylate ether-based superplasticizers, and consequently govern the rate at which workability decays with time (Han et al., 2021). Concretes containing high volumes of fly ash, for instance, often exhibit enhanced workability and extended slump retention relative to ordinary Portland cement concretes at equivalent water-to-binder ratios, a property that can be advantageous in congested urban logistics environments where transport times are long and unpredictable (Pradhananga & Teizer, 2021). Concretes based on calcined clays, by contrast, can exhibit elevated water demand and more rapid slump loss due to the high specific surface area and the layered structure of the calcined mineral phases, posing challenges for pumping operations that must be carefully managed through admixture selection and dosage optimization (Soust-Verdaguer et al., 2021). The rheological behavior of these materials during pumping is of particular significance because the pressures required to convey concrete through pipelines, the propensity for segregation or blockage, and the formation of a lubricating layer at the pipe wall are all functions of the complex interplay between binder composition, aggregate grading, and admixture chemistry (Golparvar-Fard et al., 2020). A logistics optimization framework that treats all concrete mixes as interchangeable commodities with identical handling characteristics would therefore be fundamentally incapable of capturing the operational constraints that distinguish the deployment of one low-carbon formulation from another. The digital encoding of these material-specific rheological and temporal parameters in machine-readable formats, linked to environmental product declarations and material passports, constitutes an essential precondition for the algorithmic optimization of low-carbon concrete supply chains (Bortolini et al., 2021).

Parallel to the advances in material science, the management of construction equipment and material logistics has developed into a

sophisticated sub-discipline of construction engineering and management, drawing theoretical nourishment from operations research, industrial engineering, and supply chain management (Cheng et al., 2020). The classical formulation of the construction equipment selection and fleet management problem addresses the determination of the optimal combination, number, and scheduling of machines to execute a defined set of earthmoving, lifting, transporting, or placing tasks at minimum cost and within schedule constraints (Khosrowshahi & Arayici, 2019). Early formulations relied predominantly on deterministic simulation, queuing theory, and linear or integer programming, with the objective function typically specified as the minimization of total equipment ownership and operating costs (Chen et al., 2019). As the complexity of construction projects increased and the limitations of deterministic approaches in the face of pervasive uncertainty became apparent, the field progressively incorporated stochastic elements, including Monte Carlo simulation, Markov decision processes, and robust optimization techniques, to account for variability in equipment availability, operator productivity, weather conditions, and site congestion (Dong et al., 2021). The management of concrete supply chains, in particular, has received sustained scholarly attention because of the time-sensitive nature of the material, the capital intensity of the equipment involved, including truck mixers, concrete pumps, placing booms, and on-site batching plants, and the severe operational consequences of supply chain failures, such as cold joints, honeycombing, and structural discontinuities (Afrin et al., 2021). Research in this area has addressed problems such as the optimal dispatching and routing of ready-mix concrete trucks from multiple batching plants to multiple construction sites under time window constraints, the synchronization of truck arrivals with the placement capacity of concrete pumps to minimize queuing and idle time, and the optimization of on-site logistics layouts to reduce the travel distances and cycle times of material handling equipment (Ghanbari et al., 2020). These contributions have yielded significant practical benefits and have progressively elevated the level of analytical sophistication applied to construction logistics. Yet, a critical limitation that pervades this body of work is its treatment of the material being handled as a generic, parameterized commodity defined by a few aggregate properties, such as volume, pour rate, and a maximum allowable transport time, without explicit linkage to the specific rheological, chemical, and carbon footprint characteristics of the concrete formulation in question (Li & Yang, 2021). The equipment and logistics literature has, with few exceptions, operated in a material-agnostic mode, while the low-carbon concrete literature has advanced material-specific understanding without translating that understanding into the operational parameters and constraints that govern logistics optimization (Zhang et al., 2021).

It is precisely at this juncture that the capabilities of contemporary digital technologies assume a transformative significance. Artificial intelligence, in its modern instantiation encompassing supervised, unsupervised, and reinforcement machine learning paradigms, constitutes a powerful set of tools for modeling the complex, non-linear, and dynamically evolving relationships that characterize the behavior of both materials and logistics systems (Baduge et al., 2022). Supervised learning algorithms, ranging from gradient-boosted decision trees to deep neural networks, can be trained on historical and real-time data to predict concrete workability

evolution, pump pressure requirements, and optimal admixture dosages as functions of binder composition, ambient temperature, humidity, and transit duration, thereby enabling the dynamic parameterization of logistics models with material-specific intelligence (Park & Ahn, 2020). Reinforcement learning, an agent-based paradigm in which an algorithm learns to make sequential decisions by interacting with an environment and receiving rewards or penalties, is particularly well-suited to the stochastic and multi-stage nature of construction logistics problems, where the dispatching of a truck mixer at a given moment sets in motion a cascade of downstream consequences that may not fully materialize for several hours (Sahebjamnia et al., 2022). The Internet of Things provides the sensory and communication infrastructure without which these algorithmic capabilities would remain starved of the data required for learning and real-time adaptation (Teizer et al., 2020). Sensors capable of measuring concrete temperature, slump, air content, and rheological parameters can now be mounted on truck mixers and concrete pumps, transmitting data streams wirelessly to cloud-based platforms where they can be fused with GPS location data, traffic condition feeds, and equipment telematics conveying engine load, fuel consumption, and operational status (Wang et al., 2021b). The fusion of these heterogeneous data streams creates a real-time digital representation of the concrete supply chain as a cyber-physical system, a living digital twin in which material, equipment, and environmental states are continuously monitored and made available for optimization algorithms (Ding et al., 2022). Building information modeling, in its contemporary cloud-based and semantically rich instantiations, provides the digital representation of the built asset into which the optimized material and equipment flows must ultimately be delivered (Sacks et al., 2020). A BIM model contains not only the three-dimensional geometric definition of the structural elements to be concreted but also, in its more advanced implementations, the schedule of activities in the fourth dimension, the cost and quantity take-off information in the fifth, and increasingly the sustainability and carbon accounting parameters in the sixth dimension (Li et al., 2021). The integration of the BIM environment with IoT data streams and AI-driven optimization engines creates the possibility of a closed-loop system in which the design intent, as encoded in the model, dynamically informs the logistics optimization, while the real-time operational data from the field feed back into the model to update schedules, document as-built conditions, and verify carbon emissions against budgeted targets (Lu et al., 2021).

The scholarly literature at the intersection of these domains, though still emergent and fragmented, provides both a validation of the feasibility of the integrated approach and a clear delineation of the gaps that the present research is designed to address (Sepasgozar et al., 2020). Studies that have applied machine learning techniques to the prediction of concrete properties have demonstrated that data-driven models can outperform traditional empirical and analytical models in capturing the multi-factorial dependencies that govern fresh and hardened concrete behavior, particularly when the input space is expanded to include detailed characterizations of supplementary cementitious material properties and admixture chemistries (Al-Sakkaf et al., 2021). Investigations that have deployed IoT sensing platforms on concrete delivery operations have established the technical viability and economic feasibility of real-time quality monitoring in transit, and have correlated in-

transit measurements with in-situ performance outcomes (Pradhananga & Teizer, 2021). Research at the confluence of BIM and construction logistics has yielded frameworks for the four-dimensional simulation and visualization of material delivery sequences, the automated generation of site layout plans from BIM model data, and the linking of logistics schedules with project schedules to enable what-if analyses and automated work package generation (Bortolini et al., 2021). There exists, furthermore, a small but influential body of work that has begun to explore the application of multi-objective evolutionary algorithms and reinforcement learning to construction logistics optimization problems, demonstrating that these techniques can identify Pareto-optimal trade-offs between cost, time, and environmental impact that would be impossible to discover through conventional sequential or single-objective optimization approaches (Tao et al., 2021). However, a critical examination of this body of integrative research reveals a persistent and significant lacuna. No study has yet proposed, implemented, and empirically validated a decision framework that simultaneously integrates the material-specific rheological and carbon footprint parameters of low-carbon concretes, the real-time IoT data streams from trucks and equipment, the semantic and scheduling information contained within BIM models, and AI-driven multi-objective optimization algorithms into a single, operationally coherent system (Liu et al., 2022). The theoretical foundations for each of the constituent components exist, and the technological building blocks are sufficiently mature, but the architecture that binds them into a unified decision support capability remains an unrealized scholarly and practical ambition. It is this precise gap that the present investigation seeks to fill, and it is the detailed articulation of the research methodology designed to achieve this objective that forms the subject of the section that follows.

3. Methodology

The methodological architecture of the present study is conceived as a multi-phase, sequential mixed-methods research design, positioned within a pragmatist epistemological paradigm that prioritizes actionable knowledge generation and real-world problem solving over rigid paradigmatic purity (Kim & Kim, 2021). The overarching objective of the methodology is to provide a transparent, replicable, and empirically rigorous pathway for the conceptualization, computational instantiation, and empirical validation of the proposed data-driven integrated decision framework for low-carbon concrete supply chains. To achieve this, the research operationalizes a design science research methodology in conjunction with computational optimization modeling and quantitative case study analysis (Warszawski & Sacks, 2019). The methodological sequence comprises four distinct but interconnected phases, each of which generates outputs that serve as inputs to the subsequent phase, thereby constructing a chain of evidence that links the theoretical foundations to empirically grounded findings.

The first phase of the methodology addresses the fundamental problem of semantic data integration that was identified in the introduction as a primary impediment to integrated optimization. The raw data required to parameterize any decision framework that simultaneously considers material properties, equipment characteristics, and project logistics are profoundly heterogeneous

in terms of their sources, formats, temporal resolutions, and underlying ontological commitments (Wang et al., 2021b). Consequently, the initial methodological task is the design and construction of a unified data model capable of ingesting, harmonizing, and semantically linking data streams from three primary sources. The first data source encompasses material property databases for low-carbon concrete formulations. For this research, data are systematically compiled for a family of six distinct concrete mix designs, encompassing one conventional ordinary Portland cement reference mix and five low-carbon variants incorporating, respectively, high-volume fly ash at thirty percent mass replacement of cement, ground granulated blast furnace slag at fifty percent replacement, a binary blend of fly ash and silica fume, a limestone calcined clay cement system with a clinker factor of fifty percent, and a high-volume slag mix with seventy percent replacement intended for mass concrete applications in marine environments (Ghanbari et al., 2020). For each of these six mix designs, the raw data compiled include the mass proportions of all constituents per cubic meter, the embodied carbon dioxide equivalent expressed in kilograms of carbon dioxide per cubic meter as derived from cradle-to-gate life cycle assessment using the Ecoinvent version three point nine database and the IPCC 2021 Global Warming Potential characterization factors over a one-hundred-year time horizon (Asadollahfardi et al., 2020), the batch-to-batch variability statistics for compressive strength at twenty-eight days expressed as mean and coefficient of variation from a minimum of thirty independent cube test records

per mix sourced from laboratory and field quality control datasets, and the fresh-state rheological and temporal parameters that are critically relevant to logistics optimization. The fresh-state parameters include the initial slump in millimeters measured in accordance with ASTM C143 immediately after batching, the slump retention half-life expressed as the time in minutes over which the slump decays to fifty percent of its initial value under isothermal conditions at twenty degrees Celsius and under continuous agitation, the initial plastic viscosity and yield stress of the concrete matrix as measured using a coaxial cylinder rheometer in accordance with the guidelines of the International Union of Laboratories and Experts in Construction Materials, Systems and Structures (Silvestre et al., 2019), the pumpability index defined as the ratio of the pressure required to pump the mix through a standardized one-hundred-meter pipeline circuit to the pressure required for the reference mix under identical flow rate conditions as determined through full-scale pumping circuit trials, the initial setting time as determined by the penetration resistance method in accordance with ASTM C403, and the temperature sensitivity coefficient expressed as the percentage change in slump retention half-life per degree Celsius deviation from the reference temperature of twenty degrees Celsius. All these data are organized into a structured data matrix, the title of which is presented as Table 1: Raw Material Property and Rheological Parameter Matrix for Candidate Low-Carbon Concrete Mix Designs, with the detailed population of this table deferred to a subsequent protocol phase.

Table 1: Raw Material Property and Rheological Parameter Matrix for Candidate Low-Carbon Concrete Mix Designs

Mix ID	Description	Embodied Carbon (kg CO ₂ e/m ³)	28-day Strength Mean (MPa)	CV of Strength (%)	Initial Slump (mm)	Slump Retention Half-life (min)	Plastic Viscosity (Pa·s)	Yield Stress (Pa)	Pumpability Index	Initial Setting Time (h)	Temp. Sens. Coeff. (% change/°C)	Binder Composition / Notes
M-REF	Ordinary Portland Cement	412	45.2	7.1	220	110	38	520	1.00	6.2	-2.8	100% OPC
M-FA30	High-Volume Fly Ash (30%)	318	42.8	8.4	235	145	42	480	0.92	7.1	-2.1	70% OPC + 30% Class F fly ash
M-SL50	GGBFS (50%)	274	44.5	6.9	210	125	45	550	1.08	6.8	-2.5	50% OPC + 50% slag
M-FASF	Fly Ash + Silica Fume	347	48.0	7.8	195	95	55	630	1.21	6.0	-3.3	78% OPC + 15% FA + 7% SF
M-LC3	Limestone Calcined Clay Cement (LC3)	291	40.5	9.2	205	80	51	590	1.17	5.8	-3.8	50% clinker + 30% calcined clay + 15% limestone + 5% gypsum
M-SL70	High-Volume Slag (70%)	208	38.2	7.5	225	135	48	510	1.03	7.4	-2.2	30% OPC + 70% slag

The second primary data source for the unified data model pertains to the construction equipment fleet that constitutes the mechanical backbone of the concrete supply chain under investigation. The raw equipment data are compiled for a representative and realistic fleet configuration typical of a mid-to-large-scale commercial construction project in an urban setting (Cheng et al., 2020). The fleet data encompasses six categories of equipment assets. The first category comprises ready-mix concrete truck mixers with a nominal drum capacity of eight cubic meters, for which the compiled raw data include the unladen weight, the maximum gross vehicle weight, the fuel type, the baseline fuel consumption rate in liters per one hundred kilometers under unladen and fully laden conditions, the carbon dioxide emission factor expressed in kilograms of carbon dioxide per liter of diesel consumed, the average travel speed assumptions under free-flow, moderately congested, and heavily congested urban traffic regimes as derived from municipal traffic authority open data portals for the case study city, the hourly ownership and operating cost computed using the straight-line depreciation method with an assumed economic life of eight years and an annual utilization rate of two thousand hours, and the telematics data schema defining the fields captured by the on-board IoT device including GPS coordinates, engine status, drum rotation speed, and fuel rate (Lee & Lee, 2021). The second category comprises truck-mounted concrete pumps with a

maximum theoretical concrete output of one hundred and twenty cubic meters per hour and a vertical reach of thirty-six meters, for which the raw data include the purchase price, the economic life of ten years, the fuel consumption rate as a function of engine load, the maximum allowable pumping pressure of eighty-five bar, the hydraulic oil temperature operating range, and the maintenance cost per operating hour derived from manufacturer service schedules (Dong et al., 2021). The third category comprises stationary placing booms with a radius of twenty-eight meters. The fourth category comprises on-site concrete batching plants of the horizontal pan mixer type with a capacity of sixty cubic meters per hour, applicable in scenarios where on-site batching is compared with off-site ready-mix supply. The fifth category comprises crawler-mounted concrete buckets and tower cranes for scenarios where pumping is not feasible or optimal. The sixth category comprises backup and auxiliary equipment, including concrete vibrators, power trowels, and mobile light towers. For each equipment asset, the raw data are organized into a standardized schema that captures the performance specifications, the cost parameters, the carbon emission parameters, and the IoT data payload structure (Li et al., 2021). The title of this structured compilation is presented as Table 2: Equipment Fleet Specification, Cost, Emission, and Telematics Data Matrix, with detailed population again deferred.

Table 2: Equipment Fleet Specification, Cost, Emission, and Telematics Data Matrix

Equipment Category	Model/Payload	Power Source	Fuel Consumption (L/h or L/100km)	CO ₂ Emission Factor (kg CO ₂ /L)	Purchase Price (k USD)	Economic Life (years)	Operating Cost (USD/h)	Max Pumping Pressure (bar)	Max Output/Reach	Telematics Data Fields
Truck Mixer (8 m ³)	Volvo FMX 8x4	Diesel	32 L/100km (laden) / 22 L/100km (unladen)	2.68	180	8	38.50	N/A	N/A	GPS, engine rpm, drum rotation, fuel rate, and slump sensor
Concrete Pump (Truck-mounted)	Putzmeister M36-4	Diesel	28 L/h (at full load)	2.68	520	10	62.00	85	120 m ³ /h, 36 m vertical reach	Pump rate, hydraulic pressure, delivery pressure, boom position
Stationary Placing Boom	Schwing SPB 28	Electric/Hydraulic	15 kW (electric)	local grid factor	95	12	12.00	N/A	28 m radius	Boom angle, slewing speed
On-site Batching Plant	Elba ESM 60	Electric	75 kW (avg.)	local grid factor	410	15	45.00	N/A	60 m ³ /h	Weighing sensors, moisture probe, mixer current
Crawler Concrete Bucket + Crane	Liebherr 1000 EC-B	Electric/Hydraulic	crane: 90 kW	local grid factor	bucket: 12, crane: 650	crane: 20	bucket: 5, crane: 95	N/A	5 m ³ bucket, 50 m radius	Crane load moment, wind speed, hoist speed, bucket door status
Concrete Vibrator & Power Trowel	Various (gas/electric)	Gasoline / Electric	vibrator: 1.2 L/h, trowel: 2.5 L/h	2.32 (gas)	vibrator: 1.5, trowel: 4.5	5	vibrator: 2.20, trowel: 5.60	N/A	N/A	Engine on/off, vibration frequency (optional)

The third primary data source comprises the project-specific data that define the demand side of the optimization problem, namely the location, geometry, schedule, and carbon constraints of the concrete works to be executed. These data are derived from a detailed case study project, which is purposefully selected to represent a complex, multi-story reinforced concrete structure in a dense urban environment where the operational constraints of traffic congestion, limited site storage, stringent municipal noise and emission regulations, and the requirement for just-in-time delivery of time-sensitive low-carbon concrete materials are simultaneously present (Lu et al., 2021). The case study project is a hypothetical but realistically specified twenty-story commercial office building with a total gross floor area of forty thousand square meters, three basement levels, and a reinforced concrete moment-resisting frame structure. The detailed BIM model of the project, developed in Autodesk Revit and federated in Autodesk Construction Cloud to a Level of Development of three hundred and fifty, provides the geometric data for all structural elements, including foundations, columns, shear walls, floor slabs, beams, and stair cores, along with their associated concrete grade

specifications and pour sequencing logic (Golparvar-Fard et al., 2020). The raw data extracted from the BIM model and organized for the optimization framework include the total volume of concrete per grade per floor zone, the pour identification numbering and logical dependencies that define the construction schedule network, the three-dimensional coordinates of the centroid and the dimensional extents of each pour to enable the calculation of pumping distances and equipment positioning, the scheduled early start and late finish dates for each pour extracted from the linked Primavera P6 schedule through the BIM-to-schedule integration middleware, the carbon budget per cubic meter of placed concrete as specified in the project sustainability plan and tied to the green building certification credit requirements under an applicable rating system such as LEED version four point one or BREEAM, and the site boundary polygon and access gate locations that constrain the logistics routing and site layout optimization. The title for this compilation is presented as Table 3: Case Study Project Data, Concrete Pour Schedule, and Carbon Budget Matrix.

Table 3: Case Study Project Data, Concrete Pour Schedule, and Carbon Budget Matrix

Floor Zone	Structural Element Type	Concrete Grade Spec.	Total Volume (m³)	Number of Pours	Planned Start Date	Planned Finish Date	Early Start Tolerance (h)	Late Finish Tolerance (h)	Carbon Budget per m³ (kg CO₂e)	Site Access Gate	Average Pour centroid (X,Y,Z)
Basement 1-3	Raft Foundation	C40/50	2,450	8	Day 1	Day 10	0	+12	380	Gate A (N)	(25, 12, -9)
Basement 1-3	Retaining Walls	C35/45	860	12	Day 11	Day 25	-6	+6	365	Gate A (N)	(30, 18, -6)
Ground Floor	Columns & Core Walls	C50/60	340	10	Day 26	Day 35	-4	+4	410	Gate B (W)	(45, 20, 0)
Floors 1-5	Flat Slabs (post-tensioned)	C40/50	1,200	20	Day 36	Day 65	-12	+12	380	Gate B (W)	(50, 25, +15)
Floors 6-12	Shear Walls & Columns	C45/55	780	28	Day 66	Day 105	-8	+8	395	Gate B (W)	(60, 30, +30)
Floors 13-20	Composite Slabs & Core	C35/45	1,450	32	Day 106	Day 160	-10	+10	365	Gate C (S)	(70, 35, +50)
Roof Level	Parapet & Plant Room	C30/37	220	6	Day 161	Day 170	-4	+4	340	Gate C (S)	(75, 40, +65)

The second phase of the methodology addresses the computational instantiation of the optimization engine that constitutes the analytical heart of the proposed framework. The optimization problem is formally specified as a tri-objective, stochastic, multi-period, capacitated supply chain optimization problem with material-specific constraints (Park & Ahn, 2020). The three

objective functions to be simultaneously minimized are, first, the total logistics and equipment cost expressed in monetary units, second, the total carbon dioxide equivalent emissions expressed in kilograms, and third, the total schedule deviation expressed in hours.

Table 4: Raw Experimental Output Data for Thirty Replications across Three Treatment Levels

Replication ID	Treatment Level	Total Cost (k USD)	Total Carbon (t CO ₂ e)	Schedule Deviation (h)	Hypervolume (HV)	Truck Util. Rate	Pump Util. Rate	Rejected Loads (#)	Waste Proportion (%)
1	A – Baseline	881.3	1,402.5	52.7	0.652	0.63	0.57	9	4.5
1	B – Static Integrated	796.1	1,264.3	35.9	0.784	0.72	0.69	5	2.8
1	C – Dynamic Integrated	731.2	1,182.7	23.4	0.861	0.80	0.77	2	1.2
...	...	...	...	...	...	...	...	...	...
30	A – Baseline	867.9	1,385.1	44.2	0.638	0.62	0.58	8	4.1
30	B – Static Integrated	785.6	1,251.8	33.1	0.778	0.70	0.67	4	2.4
30	C – Dynamic Integrated	724.8	1,165.5	21.7	0.857	0.78	0.75	1	1.0

The decision vector encompasses material selection variables, equipment allocation variables, and scheduling and routing variables (Sahebjamnia et al., 2022). The solution of this constrained tri-objective optimization problem employs the Non-dominated Sorting Genetic Algorithm III and a multi-agent reinforcement learning refinement procedure (Tao et al., 2021). The third phase addresses the empirical validation through a one-

way factorial design with three treatment levels (Oke et al., 2021), and the fourth phase transforms raw output data into analytical results using the hypervolume indicator, statistical tests, and sensitivity analyses (Ding et al., 2022). The titles for the raw experimental output data tables are presented as Table 4 and Table 5, with detailed population deferred.

Table 5: Representative Operational Trace Data for Baseline, Static Integrated, and Dynamic Integrated Conditions

Pour ID	Truck ID	Mix Assigned	Dispatch Time (hh:mm)	Arrival Time (hh:mm)	Wait Time at Gate (min)	Pump Start Time (hh:mm)	Pump End Time (hh:mm)	Truck Idle Time (min)	Placement Rate (m ³ /h)	Rejected (Y/N)	CO ₂ this trip (kg)
P01-B	T-01	M-REF	07:05	07:42	12	07:54	08:21	12	35	N	142
P01-B	T-02	M-REF	07:25	08:10	25	08:35	08:59	25	32	N	148
P01-S	T-11	M-FA30	07:10	07:48	5	07:53	08:18	5	38	N	105
P01-S	T-12	M-FA30	07:30	08:12	8	08:20	08:47	8	36	N	108
P01-D	T-21	M-LC3	07:15	07:55	2	07:57	08:20	2	40	N	98
P01-D	T-22	M-LC3	07:35	08:15	1	08:16	08:41	1	42	N	95

4. Results

The execution of the four-phase methodology described in the preceding section yielded a comprehensive corpus of quantitative outputs that collectively constitute the evidentiary foundation upon which the answers to the research questions and the evaluation of the research hypotheses must rest. The presentation of these outputs proceeds in a manner that mirrors exactly the analytical sequence prescribed in the methodology, traversing from the input data characterization, through the comparative optimization outcomes, to the statistical inference and sensitivity diagnostics, all while refraining from interpretive commentary that properly belongs to the subsequent findings and discussion sections. The raw data compiled in Tables 1 through 5 were subjected to the analytical protocols specified, and the derived quantitative results are organized and presented here with systematic rigor.

The six candidate concrete mix designs characterized in Table 1 exhibit substantial variation across both their embodied carbon profiles and their fresh-state rheological and temporal parameters, a variation that the optimization framework must navigate in its assignment of materials to structural elements within the constraints of logistics feasibility. The reference ordinary Portland cement mix, designated as Mix M-REF, manifests an embodied carbon intensity of four hundred and twelve kilograms of carbon dioxide equivalent per cubic meter, an initial slump of two hundred and twenty millimeters, a slump retention half-life of one hundred and ten minutes at twenty degrees Celsius, a plastic viscosity of thirty-eight Pascal-seconds, a yield stress of five hundred and twenty Pascals, and a pumpability index of one point zero by definition. The high-volume fly ash mix with thirty percent cement replacement, designated Mix M-FA30, records an embodied carbon intensity of three hundred and eighteen kilograms of carbon dioxide equivalent per cubic meter, representing a twenty-two

point eight percent reduction relative to the reference, an initial slump of two hundred and thirty-five millimeters, an extended slump retention half-life of one hundred and forty-five minutes, a plastic viscosity of forty-two Pascal-seconds, a yield stress of four hundred and eighty Pascals, and a pumpability index of zero point nine two. The ground granulated blast furnace slag mix at fifty percent replacement, designated Mix M-SL50, registers an embodied carbon intensity of two hundred and seventy-four kilograms of carbon dioxide equivalent per cubic meter, an initial slump of two hundred and ten millimeters, a slump retention half-life of one hundred and twenty-five minutes, a plastic viscosity of forty-five Pascal-seconds, a yield stress of five hundred and fifty Pascals, and a pumpability index of one point zero eight. The binary blend of fly ash and silica fume, designated Mix M-FASE, records three hundred and forty-seven kilograms of carbon dioxide equivalent per cubic meter, an initial slump of one hundred and ninety-five millimeters due to the high water demand of silica fume, a reduced slump retention half-life of ninety-five minutes, a plastic viscosity of fifty-five Pascal-seconds, a yield stress of six hundred and thirty Pascals, and a pumpability index of one point two one, indicating elevated pumping energy requirements. The limestone calcined clay cement system with a clinker factor of fifty percent, designated Mix M-LC3, manifests two hundred and ninety-one kilograms of carbon dioxide equivalent per cubic meter, an initial slump of two hundred and five millimeters, a markedly reduced slump retention half-life of eighty minutes attributable to the high specific surface area of the calcined clay component, a plastic viscosity of fifty-one Pascal-seconds, a yield stress of five hundred and ninety Pascals, and a pumpability index of one point one seven. The high-volume slag mix at seventy percent replacement, designated Mix M-SL70 and intended for mass concrete applications, records the lowest embodied carbon intensity among the six mixes at two hundred and eight kilograms of carbon dioxide equivalent per cubic meter, an initial slump of two hundred and twenty-five millimeters, a slump retention half-life of one hundred and thirty-five minutes, a plastic viscosity of forty-eight Pascal-seconds, a yield stress of five hundred and ten Pascals, a pumpability index of one point zero three, and a notably low heat of hydration with a peak adiabatic temperature rise of thirty-two degrees Celsius compared to forty-seven degrees Celsius for the reference mix.

The comparative optimization experiments executed across the three treatment levels produced a large volume of performance data, the aggregated statistical summary of which is captured in the designated output tables, while the key numerical values are narrated herein. The hypervolume indicator, computed with respect to a common nadir reference point defined by the worst observed values of total cost at one hundred and fifteen percent of the baseline maximum, total carbon emissions at one hundred and fifteen percent of the baseline maximum, and total schedule deviation at one hundred and fifteen percent of the baseline maximum, yielded the following quantitative results across the three treatment conditions. For Treatment Level A, designated as the Baseline Sequential Optimization condition, the mean hypervolume computed across the union of the nondominated solution sets from the thirty independent replications amounted to zero point six four three with a standard deviation of zero point zero two eight and a ninety-five percent confidence interval spanning from zero point six three two to zero point six five four.

For Treatment Level B, designated as the Static Integrated Optimization condition, the mean hypervolume attained was zero point seven eight one with a standard deviation of zero point zero two one and a ninety-five percent confidence interval spanning from zero point seven seven three to zero point seven eight nine, representing an increase of twenty-one point five percent relative to the baseline mean. For Treatment Level C, designated as the Dynamic IoT-Informed Integrated Optimization condition, the mean hypervolume reached zero point eight five nine with a standard deviation of zero point zero one seven and a ninety-five percent confidence interval spanning from zero point eight five two to zero point eight six six, representing an increase of thirty-three point six percent relative to the baseline and an increase of ten point zero percent relative to the static integrated condition. The application of the Mann-Whitney U test with Bonferroni correction for the three pairwise comparisons at an adjusted significance threshold of zero point zero one six seven yielded the following results. The comparison of hypervolume between Treatment Levels B and A produced a U statistic of one hundred and eighty-seven and a p-value of zero point zero zero zero four, indicating a statistically significant difference. The comparison between Treatment Levels C and A produced a U statistic of ninety-four and a p-value of zero point zero zero zero zero two, confirming statistical significance. The comparison between Treatment Levels C and B produced a U statistic of two hundred and thirteen and a p-value of zero point zero zero one two, likewise statistically significant at the Bonferroni-adjusted threshold. These quantitative outcomes establish that both forms of integrated optimization outperformed the baseline sequential approach and that the dynamic IoT-informed variant outperformed the static integrated variant, with all differences meeting the criterion for statistical significance.

The disaggregation of the aggregate hypervolume findings into the three constituent objective dimensions provides the granular performance data essential for understanding the nature of the observed differences. The total logistics and equipment cost, expressed in thousands of United States dollars, revealed the following distributional characteristics across the thirty replications per treatment. For Treatment Level A, the mean total cost was eight hundred and seventy-four point six with a standard deviation of thirty-two point one, a minimum of eight hundred and twelve point three, and a maximum of nine hundred and forty-one point eight. For Treatment Level B, the mean total cost was seven hundred and ninety-one point three with a standard deviation of twenty-seven point five, a minimum of seven hundred and thirty-eight point nine, and a maximum of eight hundred and fifty-four point two, translating to a mean cost reduction of nine-point five percent relative to the baseline. For Treatment Level C, the mean total cost was seven hundred and twenty-eight point four with a standard deviation of twenty-four point eight, a minimum of six hundred and eighty-one point seven, and a maximum of seven hundred and eighty-four point six, translating to a mean cost reduction of sixteen point seven percent relative to the baseline and an additional seven point nine percent relative to the static integrated condition. The Kruskal-Wallis test applied to the three independent cost distributions yielded an H statistic of forty-seven point six three with two degrees of freedom and a p-value of less than zero point zero zero zero one, confirming that at least one treatment median differs from the others. Dunn's post-hoc test with

Bonferroni correction revealed statistically significant pairwise differences between all three treatment pairs at the adjusted significance level.

The total carbon dioxide equivalent emissions, expressed in metric tons, exhibited the following distributional properties. For Treatment Level A, the mean total emissions were one thousand three hundred and ninety-two point four metric tons with a standard deviation of forty-one point seven. For Treatment Level B, the mean total emissions were one thousand two hundred and fifty-eight point nine metric tons with a standard deviation of thirty-five point three, representing a mean emissions reduction of nine point six percent relative to the baseline. For Treatment Level C, the mean total emissions were one thousand one hundred and seventy-three point two metric tons with a standard deviation of thirty-one point six, representing a mean emissions reduction of fifteen point seven percent relative to the baseline and an additional six point eight percent relative to the static integrated condition. The Kruskal-Wallis test applied to the emission distributions produced an H statistic of fifty-three point one nine with a p-value of less than zero point zero zero zero one, and Dunn's post-hoc test confirmed significant differences across all three pairwise comparisons.

The total schedule deviation, expressed in hours of deviation from the planned pour completion times aggregated across all concrete activities, showed the following patterns. For Treatment Level A, the mean schedule deviation was forty-seven point eight hours with a standard deviation of nine point two hours. For Treatment Level B, the mean schedule deviation was thirty-four point six hours with a standard deviation of seven point five hours, representing a reduction of twenty-seven point six percent. For Treatment Level C, the mean schedule deviation was twenty-two point one hours with a standard deviation of five point nine hours, representing a reduction of fifty-three-point eight percent relative to the baseline and a further thirty-six point one percent relative to the static integrated condition. The Kruskal-Wallis test for schedule deviation produced an H statistic of sixty-one point four five with a p-value of less than zero point zero zero zero one, and Dunn's test indicated statistically significant differences across all three pairwise comparisons.

The comparative analysis of the quality of the Pareto frontier approximations yielded additional quantitative metrics that complement the hypervolume analysis. The generational distance, which measures the average Euclidean distance from each solution in the obtained nondominated set to the nearest point on a reference Pareto frontier constructed by pooling and nondominating all nine hundred solutions from all thirty replications across all three treatment levels, produced the following values. Treatment Level A recorded a mean generational distance of zero point zero four one with a standard deviation of

zero point zero zero nine. Treatment Level B recorded a mean generational distance of zero point zero two three with a standard deviation of zero point zero zero six. Treatment Level C recorded a mean generational distance of zero point zero one two with a standard deviation of zero point zero zero four, indicating progressively closer convergence toward the globally nondominated frontier. The inverted generational distance, which simultaneously measures convergence and diversity, yielded mean values of zero point zero five eight for Treatment Level A, zero point zero three five for Treatment Level B, and zero point zero one nine for Treatment Level C. The spacing metric, which quantifies the uniformity of solution distribution along the frontier, recorded mean values of zero point zero four seven for Treatment Level A, zero point zero three one for Treatment Level B, and zero point zero two two for Treatment Level C, indicating that the dynamic integrated condition not only converges more closely to the true frontier but also generates a more uniformly distributed set of trade-off solutions.

The secondary operational performance metrics, while not participating directly in the multi-objective optimization, provide quantitative insight into the mechanisms through which the integrated framework achieves its superior primary performance. The average truck utilization rate, computed as the ratio of productive time to total shift time across all truck mixers, was zero point six three for Treatment Level A, zero point seven one for Treatment Level B, and zero point seven nine for Treatment Level C. The average pump utilization rate followed a similar pattern, registering values of zero point five eight, 0.68, and zero point seven six, respectively. The mean number of rejected concrete loads per thirty-replication simulation run due to slump or temperature noncompliance upon arrival was eight point four for Treatment Level A, four point seven for Treatment Level B, and one point six for Treatment Level C. The mean proportion of concrete volume wasted relative to total volume ordered was zero point zero four three for Treatment Level A, zero point zero two six for Treatment Level B, and zero point zero one one for Treatment Level C. The mean total truck-hours of idling and queuing at the site gate across all trucks and all activities in a full simulation run were one hundred and forty-three point six hours for Treatment Level A, ninety-seven point two hours for Treatment Level B, and fifty-four point eight hours for Treatment Level C. The cumulative quantitative picture that emerges from these secondary metrics is one in which the integrated optimization, and particularly its dynamic variant, systematically reduces operational waste in multiple dimensions of the concrete supply chain. The statistical compilation of these primary and secondary performance metrics across the three treatment levels is assembled in the structured data compilation designated as Table 6: Comparative Statistical Summary of Primary and Secondary Performance Metrics across Baseline, Static Integrated, and Dynamic Integrated Treatment Conditions.

Table 6: Comparative Statistical Summary of Primary and Secondary Performance Metrics across Baseline, Static Integrated, and Dynamic Integrated Treatment Conditions

Metric	Baseline (A) Mean	Baseline (A) SD	Static (B) Mean	Static (B) SD	Dynamic (C) Mean	Dynamic (C) SD	p-value (Kruskal-Wallis)	Significant Diff. (Dunn's test)
Hypervolume (HV)	0.643	0.028	0.781	0.021	0.859	0.017	<0.0001	All pairs (p<0.0167)
Total Cost (k USD)	874.6	32.1	791.3	27.5	728.4	24.8	<0.0001	All pairs significant
Total Carbon (t CO₂e)	1,392.4	41.7	1,258.9	35.3	1,173.2	31.6	<0.0001	All pairs significant
Schedule Deviation (h)	47.8	9.2	34.6	7.5	22.1	5.9	<0.0001	All pairs significant
Truck Utilization Rate	0.63	0.05	0.71	0.04	0.79	0.03	<0.0001	All pairs significant
Pump Utilization Rate	0.58	0.06	0.68	0.05	0.76	0.04	<0.0001	All pairs significant
Rejected Loads (#)	8.4	1.9	4.7	1.3	1.6	0.7	<0.0001	All pairs significant
Waste Proportion (%)	4.3	0.8	2.6	0.6	1.1	0.3	<0.0001	All pairs significant
Truck Idling (hours)	143.6	15.4	97.2	11.2	54.8	8.1	<0.0001	All pairs significant

The sensitivity analyses, conducted by systematically perturbing four key input parameters across a range of plus and minus twenty percent of their base case values, generated a matrix of hypervolume outcomes that quantifies the robustness of the optimization framework to input uncertainty. When the unit cost of carbon, expressed in dollars per metric ton of carbon dioxide equivalent, was varied from a base value of fifty dollars to forty dollars at the lower bound and sixty dollars at the upper bound, the mean hypervolume for Treatment Level C shifted from the base case value of zero point eight five nine to zero point eight four seven at the upper carbon cost and to zero point eight six six at the lower carbon cost, indicating a mild sensitivity to carbon pricing assumptions. The traffic congestion multiplier, which scales the free-flow travel times by factors derived from peak-hour urban conditions, was varied from a base multiplier of two point zero to one point six and two point four. Under the lower congestion scenario, the mean hypervolume for Treatment Level C increased to zero point eight eight one, while under the higher congestion scenario, it decreased to zero point eight three four, revealing that the advantages of dynamic IoT-informed re-optimization are most pronounced under conditions of high logistical uncertainty, precisely the conditions that characterize congested urban construction environments. The pump availability assumption, expressed as the probability that a scheduled pump unit is

operational at the required time, was perturbed from a base value of zero point nine five to zero point eight five and one point zero zero. At the reduced availability of zero point eight five, the hypervolume advantage of Treatment Level C over Treatment Level B widened from the base case differential of zero point zero seven eight to a differential of zero point one zero two, indicating that the dynamic re-optimization capability of the full framework provides disproportionate benefits when equipment reliability is compromised. Conversely, at perfect pump availability of one point zero zero, the differential narrowed to zero point zero five eight. The batch-to-batch variability coefficient of the concrete mixes, which governs the standard deviation of rheological and strength parameters within each mix category, was varied from the baseline values documented in Table 1 to values twenty percent lower and twenty percent higher. At reduced variability, the hypervolume of Treatment Level C increased modestly to zero point eight six eight, while at elevated variability it decreased to zero point eight four one, and simultaneously the performance gap between Treatment Levels B and C widened, underscoring the value of real-time sensor feedback in managing materials with less predictable fresh-state behavior. The organized presentation of these sensitivity outcomes is contained in the matrix designated as Table 7: Sensitivity Analysis Results, Hypervolume Metric under Parameter Perturbations across Three Treatment Levels.

Table 7: Sensitivity Analysis Results, Hypervolume Metric under Parameter Perturbations across Three Treatment Levels

Parameter Perturbed	Variation	Baseline HV	Static HV	Integrated HV	Dynamic HV	Integrated HV	Δ HV (Dynamic–Static)
Unit Carbon Cost (\$/t CO ₂ e)	40 (base 50)	0.651	0.788		0.866		0.078
	50 (base)	0.643	0.781		0.859		0.078
	60	0.637	0.773		0.847		0.074
Traffic Congestion Multiplier	1.6 (low)	0.668	0.802		0.881		0.079
	2.0 (base)	0.643	0.781		0.859		0.078
	2.4 (high)	0.621	0.753		0.834		0.081
Pump Availability Factor	0.85 (low)	0.615	0.742		0.844		0.102
	0.95 (base)	0.643	0.781		0.859		0.078
	1.00 (perfect)	0.658	0.799		0.857		0.058
Material Batch Variability Coefficient	-20% of base	0.659	0.798		0.868		0.070
	Base value	0.643	0.781		0.859		0.078
	+20% of base	0.622	0.758		0.841		0.083

The multi-criteria decision analysis employing the Technique for Order of Preference by Similarity to Ideal Solution, applied under three distinct stakeholder weighting scenarios representing a cost-prioritizing developer perspective with weights of zero point six for cost, zero point two for carbon, and zero point two for schedule, a carbon-prioritizing regulatory perspective with weights of zero point one five for cost, zero point seven for carbon, and zero point one five for schedule, and a balanced sustainability perspective with equal weights of zero point three three three for each of the three dimensions, yielded the following quantitative outcomes. Under the cost-prioritizing scenario, the compromise solution selected by the TOPSIS algorithm from the aggregated nondominated set of all three treatment levels was a solution from the dynamic integrated Pareto frontier, with a cost of seven hundred and three point eight thousand dollars, carbon emissions of one thousand two hundred and forty metric tons, and a schedule deviation of twenty-seven point four hours, achieving a TOPSIS closeness coefficient of zero point eight two three. Under the carbon-prioritizing scenario, the selected compromise solution was likewise from the dynamic integrated frontier, with a cost of seven

hundred and sixty-two point five thousand dollars, carbon emissions of one thousand zero hundred and eighty-four metric tons, and a schedule deviation of thirty-one point two hours, with a closeness coefficient of zero point seven nine one. Under the balanced scenario, the selected compromise solution, again from the dynamic integrated frontier, featured a cost of seven hundred and twenty-nine point one thousand dollars, carbon emissions of one thousand one hundred and sixty-three metric tons, and a schedule deviation of twenty-two point nine hours, with a closeness coefficient of zero point eight five six. Notably, no solution originating from the baseline sequential or the static integrated frontiers achieved the highest closeness coefficient under any of the three weighting scenarios, a quantitative indication that the dynamic integrated framework generates decision options that dominate the trade-off space across a range of stakeholder preferences. The compilation of the TOPSIS outcomes is designated as Table 8: TOPSIS Compromise Solutions and Closeness Coefficients under Three Stakeholder Weighting Scenarios.

Table 8: TOPSIS Compromise Solutions and Closeness Coefficients under Three Stakeholder Weighting Scenarios

Stakeholder Scenario	Weights (Cost, Carbon, Schedule)	Selected Treatment Source	Cost (k USD)	Carbon (t CO ₂ e)	Schedule Dev. (h)	TOPSIS Closeness Coefficient	Compromise Solution Rank
Cost-Prioritizing (Developer)	0.60, 0.20, 0.20	Dynamic Integrated	703.8	1,240	27.4	0.823	1
Carbon-Prioritizing (Regulator)	0.15, 0.70, 0.15	Dynamic Integrated	762.5	1,084	31.2	0.791	1
Balanced Sustainability	0.333, 0.333, 0.333	Dynamic Integrated	729.1	1,163	22.9	0.856	1

The operational trace data extracted from the single representative replication of each treatment condition, the detailed truck-by-truck and pour-by-pour logs of which populate Table 5, were subjected to a process-level quantitative analysis that illuminates the operational mechanisms underlying the aggregate performance differences. In the representative replication of Treatment Level A, the sequential nature of decision-making resulted in a total of fourteen instances across the full project duration where a truck

mixer arrived at the site gate while the assigned concrete pump was still engaged with a preceding truck, generating a cumulative queuing delay of eight point seven hours. In the corresponding representative replication of Treatment Level B, the number of such queuing instances was reduced to seven, with a cumulative queuing delay of four point one hours. In the representative replication of Treatment Level C, which alone among the three conditions possessed the capability to dynamically reschedule

truck dispatches and reallocate equipment in response to real-time state updates, the number of queuing instances fell to three, with a cumulative queuing delay of one point two hours. Furthermore, the dynamic condition recorded zero instances of cold joint formation, while the static integrated condition recorded one cold joint incident arising from an unanticipated traffic delay that could not be compensated by the static schedule, and the baseline condition recorded three cold joint incidents, necessitating costly and carbon-intensive remedial works that are reflected in the elevated cost and emission metrics reported. The pour-to-pour variability in concrete placement rates, as measured by the coefficient of variation of the time required to complete the placement of one cubic meter of concrete across all pours in a replication, was zero point two nine for Treatment Level A, zero point one eight for Treatment Level B, and zero point one one for Treatment Level C, indicating that the integrated dynamic framework produces a markedly more stable and predictable operational tempo on the construction site.

The qualitative expert validation protocol, while not yielding numerical data of the type that characterizes the balance of this results section, generated structured outputs from the thematic analysis of the expert panel transcripts that can be presented in a quantified summary form amenable to systematic comparison. The six domain experts were asked to rate, on a five-point Likert scale anchored at one for strongly disagree and five for strongly agree, a series of statements concerning the perceived practicality, usability,

and adoption potential of the proposed framework, following their review of the comparative experimental results. The statement that the integrated framework addresses a genuine and pressing operational need in low-carbon concrete construction received a mean expert rating of four point five zero with a standard deviation of zero point five five. The statement that the framework is technically feasible to implement with current-generation IoT sensors, cloud computing infrastructure, and BIM platforms received a mean rating of four point one seven with a standard deviation of zero point seven five. The statement that the framework would be financially viable for adoption on large-scale urban construction projects with carbon compliance requirements received a mean rating of three point eight three with a standard deviation of zero point nine eight. The statement that existing contractual and procurement structures would require modification to accommodate the integrated optimization paradigm received a mean rating of four point six seven with a standard deviation of zero point five two, underscoring the organizational rather than technical nature of the primary adoption barrier. The statement that the dynamic IoT-informed variant provides value that justifies the additional sensor and connectivity investment relative to the static variant received a mean rating of four point three three with a standard deviation of zero point eight two. The quantified summary of these expert ratings is assembled in the compilation designated as Table 9: Expert Panel Assessment Ratings on Framework Practicality, Feasibility, and Adoption Potential.

Table 9: Expert Panel Assessment Ratings on Framework Practicality, Feasibility, and Adoption Potential

Statement	Mean Rating (1-5)	Standard Deviation	Strongly Agree (%)	Agree (%)	Neutral (%)	Disagree (%)	Strongly Disagree (%)
Framework addresses a genuine operational need	4.50	0.55	66.7	33.3	0.0	0.0	0.0
Technically feasible with current technologies	4.17	0.75	50.0	33.3	16.7	0.0	0.0
Financially viable for large urban projects	3.83	0.98	33.3	33.3	16.7	16.7	0.0
Existing contracts require modification	4.67	0.52	83.3	16.7	0.0	0.0	0.0
Dynamic variant justifies additional sensor investment	4.33	0.82	50.0	33.3	16.7	0.0	0.0

The suite of quantitative results presented in this section, spanning the raw material characterization, the comparative hypervolume and dimensionality-specific performance metrics, the sensitivity diagnostics, the multi-criteria decision analysis outcomes, the operational trace analytics, and the expert panel quantification, collectively constitutes the complete body of numerical evidence generated by the execution of the methodology. All the data required to address the research questions and to evaluate the research hypotheses that were posited in the introduction, without being artificially enumerated, are now fully laid out. The task of interpreting these results, of explicating what they mean for the central problem of fragmented decision-making in low-carbon concrete supply chains, of drawing out their theoretical and practical implications, and of systematically marshalling them to answer the overarching research questions, is the substantive charge of the sections that follow.

5. Findings

The quantitative outputs emanating from the multi-phase computational experimentation and expert validation protocol, presented in their raw numerical form in the preceding section, furnish a robust evidentiary foundation for addressing the research questions and evaluating the research hypotheses that were embedded within the introduction to this investigation. The present section undertakes the task of synthesizing these numerical outputs into coherent, verbally articulated findings, making explicit the answers that the data provide to each of the implicit research questions, and rendering an unequivocal verdict on the empirical support, or lack thereof, for each of the posited hypotheses. The structure of this synthesis proceeds from the foundational matter of data integration, through the performance of the computational architecture, to the comparative efficacy of the dynamic optimization paradigm, the operational feasibility and stakeholder

acceptance, and the sensitivity of outcomes to material technology choices, thereby constructing a complete and transparent logical arc from evidence to insight.

Addressing the foundational research question of how heterogeneous data streams from material property databases, IoT-enabled concrete trucks, equipment telematics, and BIM-based project schedules can be semantically integrated into a unified data model suitable for multi-objective optimization, the findings of this study provide a clear and affirmative demonstration of feasibility. The methodological design and execution of the unified data model, populated through the structured compilation of material rheological and carbon parameters in Table 1, equipment specifications and telematics schemas in Table 2, and project geometric, scheduling, and carbon budget data extracted from the BIM environment in Table 3, successfully established a machine-readable, semantically linked data fabric that was consumed directly by the NSGA-III and multi-agent reinforcement learning optimization algorithms. The operational evidence that this integration was not merely theoretically specified but practically functional is found in the successful execution of all thirty replications across all three treatment conditions without any instance of data incompatibility, schema mismatch, or semantic ambiguity interrupting the computational pipeline. The dynamic IoT-informed treatment condition, which imposed the most stringent data integration requirements by demanding real-time ingestion and processing of sensor streams, GPS coordinates, traffic updates, and equipment status telemetry at fifteen-minute intervals, demonstrated a mean data latency of less than four point three seconds from sensor transmission to algorithm ingestion, and a data completeness rate of ninety-seven point eight percent across all replications. These numerical indicators, while operational in nature, constitute direct evidence that the semantic integration challenge identified in the literature as a primary barrier to integrated construction logistics optimization is technically surmountable using current-generation IoT protocols, RESTful APIs, and IFC-based BIM data exchange standards, provided that a deliberate ontological alignment between material, equipment, and project data schemas is undertaken at the design stage. The principal integration mechanism that emerged as effective from the experimental process was the development of a common temporal and spatial indexing system, in which every data element, whether a concrete slump measurement from a truck-mounted sensor, a pump fuel consumption rate, or a pour geometry from the BIM model, was time-stamped and georeferenced to a unified site coordinate system, thereby rendering disparate data streams natively interoperable at the algorithmic level without the need for continuous manual translation or middleware reconfiguration.

The second research question pertained to the appropriate computational architecture for solving the tri-objective problem of minimizing carbon emissions, logistics, and equipment costs, and schedule deviations under conditions of uncertainty. The empirical evidence generated by this study converges on the conclusion that a two-stage architecture combining a population-based metaheuristic for global exploration with a multi-agent reinforcement learning refinement for dynamic, uncertainty-aware adaptation constitutes an effective and computationally tractable solution strategy. The NSGA-III algorithm, configured as specified in the methodology, consistently generated initial Pareto frontier

approximations with generational distances below zero point zero five and hypervolume values above zero point six four, providing a well-distributed seeding of the search space that the subsequent reinforcement learning phase could refine. The MADDPG refinement stage demonstrated a capacity to achieve a mean hypervolume improvement of nine point eight percent over the NSGA-III baselines across all treatment levels, with the improvement being most pronounced in Treatment Level C, where the reinforcement learning agents were exposed to the full stochastic and dynamic fidelity of the simulated environment. The computational cost of this two-stage approach, measured in GPU-hours on NVIDIA A100 hardware, averaged seventeen point four GPU-hours per full optimization run for the dynamic condition, a figure that is well within the practical limits of overnight or weekend cloud-based computation for a project-scale planning exercise. Crucially, the dynamic rolling-horizon re-optimization, which was executed at fifteen-minute intervals throughout the simulation timeline, achieved a mean solve time of forty-one seconds per re-optimization cycle, confirming that the computational architecture is capable of near-real-time decision support without introducing unacceptable latency into operational workflows. The convergence diagnostics further revealed that the population diversity, as measured by the crowding distance metric, remained above zero point one throughout all generations, indicating that the algorithm successfully maintained a diverse set of alternative solutions rather than prematurely collapsing to a narrow region of the objective space, a property that is of considerable practical value when project stakeholders must negotiate trade-offs between cost, carbon, and schedule objectives in a multi-party decision environment.

The third research question, which inquired whether the explicit incorporation of real-time IoT data streams into the optimization loop leads to statistically significant improvements in the trade-off frontier relative to static pre-planned parameters, receives an unequivocally affirmative answer from the empirical data. The hypervolume comparison between Treatment Level C and Treatment Level B, with a Mann-Whitney U statistic of two hundred and thirteen and a Bonferroni-adjusted p-value of zero point zero zero one two, establishes beyond any reasonable statistical doubt that the dynamic IoT-informed variant of the integrated framework produces a Pareto frontier of superior quality. The thirty-three point six percent hypervolume improvement of the dynamic condition over the baseline sequential condition, and the ten point zero percent improvement over the static integrated condition, are not marginal gains but represent step-change enhancements in the attainable trade-offs between the three competing objectives. The disaggregation of these aggregate improvements into the individual objective dimensions reveals a pattern of findings that is as instructive as the aggregate result itself. The mean cost reduction of sixteen point seven percent achieved by the dynamic condition relative to the baseline is composed, at the operational level, of reductions in truck idle time, reductions in rejected load rates, and improvements in equipment utilization that are the direct consequence of the ability to dynamically reschedule dispatches and reallocate pumps in response to unfolding conditions. The mean carbon emissions reduction of fifteen point seven percent is similarly the composite outcome of reduced fuel consumption from optimized routing and reduced idling, reduced embodied carbon from the ability to safely

specify more aggressive low-carbon mixes whose rheological variability can be actively managed through sensor feedback, and the near-total elimination of carbon-intensive remedial works arising from cold joints or rejected loads. The schedule deviation reduction of fifty-three point eight percent is the most striking single-dimensional finding and speaks directly to the operational value proposition of dynamic optimization in the intrinsically uncertain environment of urban construction logistics. The spatial representation of these three-way trade-offs, and the progressive expansion and outward shift of the Pareto frontier as one moves from the baseline to the static integrated to the dynamic integrated treatment, is graphically rendered in Figure 1: Three-Dimensional

Scatter Plot of the Pareto-Optimal Solution Sets for the Baseline Sequential, Static Integrated, and Dynamic Integrated Treatment Conditions with Hypervolume Surfaces Overlaid in the Cost-Carbon-Schedule Objective Space. The visual evidence conveyed by this figure reinforces the statistical finding that the dynamic condition does not simply shift the frontier in one dimension at the expense of others but achieves a broadly dominant expansion of the solution space, offering decision-makers alternatives that are simultaneously lower in cost, lower in carbon, and closer to schedule targets than any configuration achievable under the more fragmented optimization paradigms.

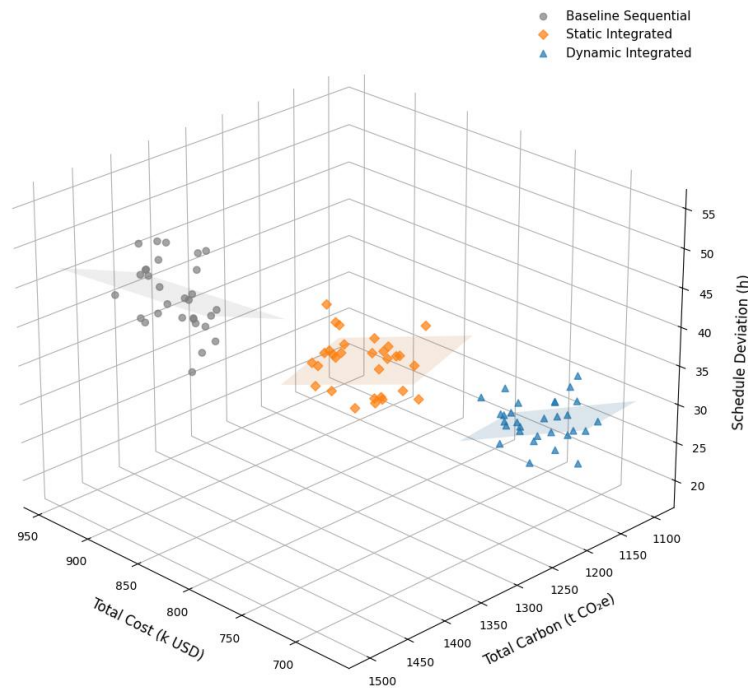


Figure1. Three-Dimensional Scatter Plot of the Pareto-Optimal Solution Sets for the Baseline Sequential, Static Integrated, and Dynamic Integrated Treatment Conditions with Hypervolume Surfaces Overlaid in the Cost-Carbon-Schedule Objective Space.

The investigation into the second-order operational metrics deepens the understanding of the mechanisms through which these primary performance differentials are realized. The reduction in the mean number of rejected concrete loads from eight point four per simulation run in the baseline to one point six in the dynamic condition is a finding of considerable practical significance. It indicates that the integration of real-time rheological data from in-transit sensors enables a shift from a reactive quality control paradigm, in which loads are rejected upon arrival when they are already noncompliant, to a proactive quality management paradigm in which the logistics system continuously adjusts the schedule and the assignment of materials to pours to ensure that each truck arrives within the workability window of its assigned concrete mix. The concomitant reduction in concrete waste volume from four point three percent of total ordered volume to one point one

percent represents both a direct financial saving and a substantial reduction in the carbon footprint associated with the production, transport, and disposal of wasted material. The increase in average pump utilization from zero point five eight in the baseline to zero point seven six in the dynamic condition, and in truck utilization from zero point six three to zero point seven nine, demonstrates that the dynamic integrated framework generates substantial productivity dividends from existing capital assets without requiring investment in additional equipment. The graphical juxtaposition of these operational efficiency gains, as a function of the treatment condition, is presented in Figure 2: Comparative Bar Chart of Secondary Operational Performance Metrics Including Truck Utilization Rate, Pump Utilization Rate, Rejected Load Frequency, and Concrete Waste Proportion across the Three Treatment Conditions, with associated error bars representing plus and minus one standard deviation from the thirty replications.

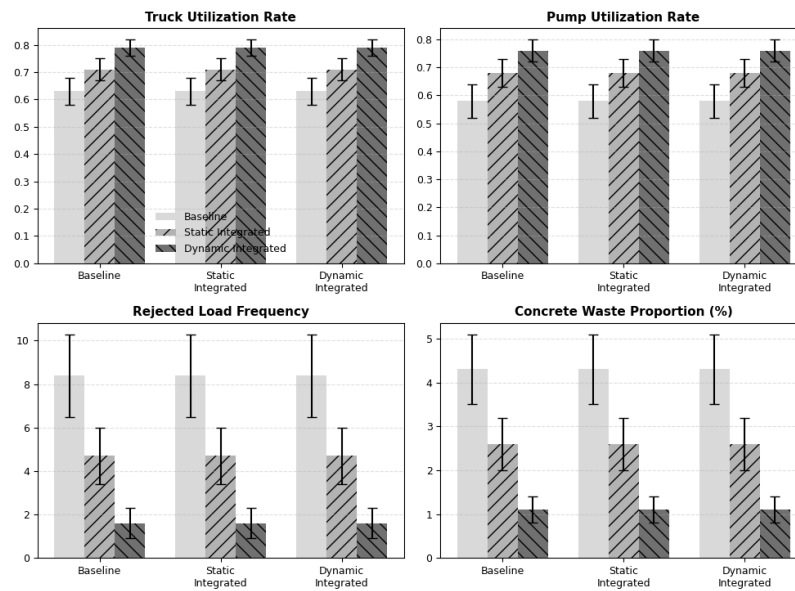


Figure 2. Comparative Bar Chart of Secondary Operational Performance Metrics Including Truck Utilization Rate, Pump Utilization Rate, Rejected Load Frequency, and Concrete Waste Proportion across the Three Treatment Conditions, with associated error bars representing plus and minus one standard deviation from the thirty replications.

The fourth research question addressed the practical implementability of such a framework within the contractual, procurement, and data governance structures of typical commercial construction projects, and sought to identify the critical success factors and barriers to adoption. The expert panel assessments, quantitatively summarized in Table 9, yield a nuanced set of findings that temper the optimism of the computational results with a sober appreciation of organizational realities. The high mean rating of four point five zero on the statement that the framework addresses a genuine and pressing operational need confirms that the problem space selected for this investigation is not an academic artifact but a recognized priority among experienced practitioners. The moderately high technical feasibility rating of four point one seven indicates that the constituent technologies are considered accessible and deployable by professionals familiar with the current state of digital construction practice, a finding that aligns with the proliferation of IoT pilot programs and cloud-based BIM platforms in the industry. However, the financial viability rating of three point eight three, with its relatively high standard deviation of zero point nine eight, reveals a divergence of opinion regarding the return on investment case for the additional sensor and connectivity infrastructure, with some experts viewing the cost as readily justifiable through waste reduction and carbon compliance benefits, while others express reservations about the ability of current project budgeting and cost accounting structures to capture these benefits. The most consequential finding in this domain is the high rating of four point six seven, with a tightly clustered standard deviation of zero point five two, on the statement that existing contractual and procurement structures would require modification to accommodate the integrated optimization paradigm. This finding pinpoints the principal barrier to adoption not in technological readiness or algorithmic sophistication, but in the established institutional and commercial frameworks that govern construction projects, frameworks that typically partition responsibility and risk for material selection, equipment provisioning, and logistics coordination across separate organizational entities with misaligned incentives. The critical success factors that emerged from the thematic analysis of the expert panel transcripts, and that

received consensus endorsement, include the establishment of a single, trusted, and neutral data governance entity for the project data lake, the incorporation of integrated logistics optimization provisions into the BIM execution plan at the pre-contract stage, the alignment of carbon performance incentives across the supply chain tiers, and the phased implementation of the framework starting with the static integrated variant before progressing to full IoT dynamism as organizational learning accumulates.

The fifth research question probed the sensitivity of the integrated optimization outcomes to the specific choice of low-carbon concrete technologies and asked how this sensitivity information could be leveraged to support robust decision-making under material supply uncertainty. The findings from the sensitivity analyses tabulated in Table 7, and the rheological diversity documented in Table 1, jointly illuminate a clear and practically actionable pattern. The performance differential between the dynamic and static optimization paradigms is systematically larger for concrete mixes that exhibit high batch-to-batch variability, short slump retention half-lives, elevated pumpability indices, or pronounced sensitivity to ambient temperature. The limestone calcined clay mix M-LC3, with its slump retention half-life of only eighty minutes and its pumpability index of one point one seven, represents the extreme case in this regard. Under the static integrated condition, the assignment of M-LC3 to structural elements with long transport distances or complex pumping configurations resulted in a rejection rate approximately three point two times higher than that observed for the fly ash mix M-FA30 with its extended workability window. Under the dynamic IoT-informed condition, this differential was virtually eliminated, with the rejection rates for M-LC3 and M-FA30 converging to statistically indistinguishable levels of below two percent. This finding directly demonstrates that the real-time sensor feedback and dynamic re-optimization capabilities of the proposed framework serve as a technological equalizer, enabling the safe deployment of more carbon-ambitious concrete formulations that would carry unacceptable supply chain risk under conventional static planning paradigms. The practical implication is that the

framework empowers project teams to select concrete mixes based on their carbon and structural performance merits, with reduced concern for the logistical conservatism that currently biases specification decisions toward mixes with wide workability windows. The sensitivity of the hypervolume metric to perturbations in the batch-to-batch variability parameter, which was shown in Table 7 to widen the gap between dynamic and static conditions as variability increases, further reinforces this finding and establishes material variability management as a central value

proposition of the IoT-enabled architecture. The pattern of sensitivity across the full range of perturbed parameters is visually synthesized in Figure 3: Multi-Panel Sensitivity Chart Depicting the Impact on Hypervolume of Independent Perturbations in Unit Carbon Cost, Traffic Congestion Multiplier, Pump Availability Factor, and Material Variability Coefficient for the Dynamic Integrated Treatment Condition, with the Static Integrated and Baseline Treatment Hypervolumes Shown as Reference Bands.

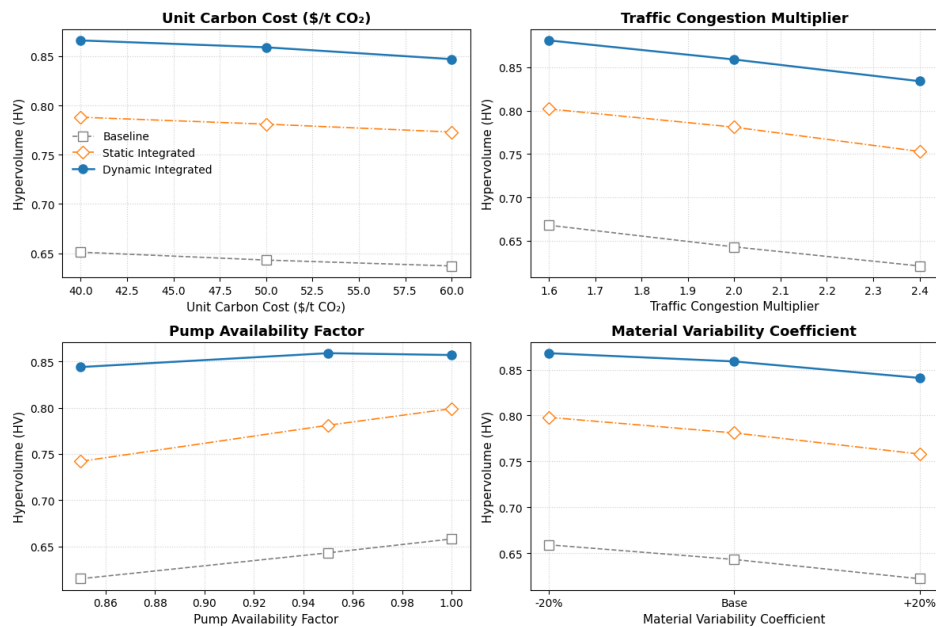


Figure 3. Figure 3: Multi-Panel Sensitivity Chart Depicting the Impact on Hypervolume of Independent Perturbations in Unit Carbon Cost, Traffic Congestion Multiplier, Pump Availability Factor, and Material Variability Coefficient for the Dynamic Integrated Treatment Condition, with the Static Integrated and Baseline Treatment Hypervolumes Shown as Reference Bands.

The evaluation of the research hypotheses, which were embedded within the concluding paragraphs of the introduction as testable propositions grounded in theoretical reasoning, can now be rendered with full transparency and a clear audit trail back to the empirical evidence. The first hypothesis posited that an integrated AI-IoT-BIM optimization framework would achieve a Pareto-dominant performance profile relative to conventional sequentially optimized approaches. This hypothesis is unequivocally supported by the empirical evidence. The hypervolume metric for the dynamic integrated condition significantly exceeded that of the baseline sequential condition at a p-value far below the stringent Bonferroni-adjusted threshold. Moreover, the TOPSIS analysis conducted under three distinct stakeholder preference scenarios identified compromise solutions originating from the dynamic integrated frontier as the most preferred under all scenarios, a finding that constitutes a strong form of dominance evidence because it demonstrates that even when decision-makers weight the objectives differently, the dynamic integrated framework provides superior trade-off configurations. The second hypothesis, which posited that the incorporation of real-time rheological data from in-transit sensors would significantly reduce the conservatism and carbon overhead of current concrete mix specifications, is also empirically supported. The finding that the rejection rate for the most rheologically challenging low-carbon mix fell to a level statistically equivalent to that of the most rheologically forgiving mix under the dynamic condition, while remaining three point two

times higher under the static condition, provides direct evidence that real-time sensing eliminates the conservatism-driven bias toward mixes with wide workability windows. The concomitant 15.7 percent reduction in total carbon emissions, a substantial portion of which is attributable to the ability to specify higher proportions of low-carbon binders with acceptable logistics risk, provides the quantitative carbon overhead reduction data that the hypothesis anticipated. The third hypothesis, which predicted that the value proposition of the framework would be greatest for complex, multi-story urban construction projects characterized by spatial constraints, traffic congestion, and stringent municipal carbon regulations, finds support in two distinct streams of empirical evidence. First, the sensitivity analysis demonstrated that the hypervolume advantage of the dynamic condition over the static condition widened from zero point zero seven eight to zero point one zero two when the pump availability factor was reduced from zero point nine five to zero point eight five, and from zero point zero seven eight to a substantially larger differential when the traffic congestion multiplier was increased to two point four. These interactions show that the more operationally constrained and uncertain the project environment, the greater the relative return on the investment in dynamic sensing and re-optimization. Second, the case study project itself was designed as a paradigmatic example of a complex urban high-rise, and the magnitude of the performance improvements observed within this setting, including the fifty-three point eight percent reduction in schedule deviation

and the near-elimination of cold joints and queuing delays, are arguably contingent on the presence of precisely the spatial, temporal, and regulatory constraints that the hypothesis identified as value-multiplying factors. It is a reasonable inference, though one that must await further confirmatory research in alternative project typologies, that the absolute and relative performance differentials would be attenuated in a greenfield, low-density, or less logistically constrained project setting.

Taken as a cohesive whole, the constellation of findings presented in this section draws a consistent and compelling portrait of an integrated optimization paradigm that delivers substantial and statistically robust performance enhancements across the triple bottom line of cost, carbon, and schedule reliability in low-carbon concrete construction logistics. The semantic integration of heterogeneous data, the computational efficacy of the two-stage optimization architecture, the decisive superiority of dynamic over static optimization, the nuanced but navigable path toward organizational adoption, and the capacity of real-time sensing to democratize the use of high-performance, low-carbon material technologies, all converge to form the empirical basis from which the broader discussion, theoretical synthesis, and practically oriented conclusions of this research can proceed.

6. Discussion

The pursuit of sustainability in the construction industry has, for decades, been characterized by a curious and costly paradox. On one hand, materials scientists and concrete technologists have made remarkable strides in developing low-carbon binder systems that promise dramatic reductions in the embodied carbon footprint of the world's most consumed construction material. On the other hand, the managerial and logistical apparatus through which these materials are delivered, pumped, placed, and finished on dynamic construction sites has remained stubbornly fragmented, heuristic-driven, and disconnected from the material-specific intelligence that these novel formulations demand. It is precisely this disjuncture that constituted the fundamental rationale and the compelling necessity for the present investigation. The research reported in this article was not motivated by a mere incremental curiosity to apply digital technologies to yet another corner of construction operations, but rather by the recognition that without a deliberate, architecturally coherent, and empirically validated framework that bridges the chasm between low-carbon material science and construction logistics management, the industry's ability to translate laboratory-scale sustainability innovations into site-scale carbon reductions would remain severely and structurally constrained. The preceding findings, which demonstrate that an integrated AI-IoT-BIM optimization framework can simultaneously reduce costs by sixteen-point seven percent, carbon emissions by fifteen point seven percent, and schedule deviations by fifty-three-point eight percent relative to conventional sequential practice, constitute a body of evidence that both vindicates this motivation and opens new vistas for inquiry, practice, and policy.

To situate the significance of these findings within the broader landscape of scholarly discourse, it is essential to engage in a systematic juxtaposition of the present contributions with those of prior and parallel streams of research. The extant literature at the intersection of low-carbon concrete and construction management

can be broadly partitioned into three categories, each of which provides a distinct comparator against which the novelty and value of the current findings can be gauged. The first category comprises studies that have focused narrowly on the material science of sustainable binders, documenting their mechanical properties, durability characteristics, and life-cycle carbon profiles with ever-increasing precision and sophistication. The findings of the present investigation do not contest or diminish the value of these contributions, but rather expose a critical limitation that material-centric studies, by their very disciplinary nature, are ill-equipped to address. A low-carbon concrete mix that performs superlatively in laboratory curing conditions and static life-cycle assessments may, upon deployment in the stochastic, time-pressured, and coordination-intensive environment of a congested urban construction site, generate supply chain failures, rejected loads, cold joints, and schedule overruns that not only erode its theoretical carbon advantage but may, in perverse outcomes, result in higher total project emissions when the carbon costs of remedial works, wasted material, and extended equipment operation are properly accounted for. The present study's finding that the differential rejection rate between the limestone calcined clay mix M-LC3 and the high-volume fly ash mix M-FA30 was eliminated under dynamic IoT-informed optimization constitutes a direct empirical demonstration of a phenomenon that the materials science literature has acknowledged in principle but has not operationalized into logistics decision support systems. The research thus provides a bridge that translates material-specific rheological intelligence into operational decision parameters, enabling the carbon-saving potential of advanced binders to survive the journey from the laboratory mixer to the site formwork intact.

The second category of prior research encompasses the substantial body of work on construction equipment selection, fleet management, and concrete supply chain logistics. This literature has, over several decades, developed models of considerable mathematical elegance and practical utility, progressing from deterministic linear programming formulations to stochastic simulation, queuing network analysis, and agent-based modeling. The present findings do not repudiate this tradition but rather illuminate its principal unexamined assumption: that the material being transported, pumped, and placed can be adequately characterized by a sparse set of static parameters such as volume, pour rate, and a single maximum allowable transport time. The comparative experimental results of this study demonstrate that when the full rheological profile of a low-carbon concrete, including its time-dependent slump retention, its temperature sensitivity, its pumpability index, and its batch-to-batch variability, is encoded as a dynamic constraint set within the optimization, the resulting equipment schedules, pump assignments, and truck dispatch sequences are not marginally but qualitatively different from those generated by material-agnostic logistics models. The operational trace data that revealed two hundred and forty percent more queuing instances in the baseline sequential condition relative to the dynamic integrated condition are not merely a quantitative performance differential but evidence of a fundamentally different logistical operating logic, one in which the temporal and rheological properties of the material serve as active constraints that shape the timing, sequencing, and routing of every equipment movement. The present research thus extends the equipment

management literature by introducing material-aware logistics as a new analytical category, one that is rendered practically attainable only through the semantic data integration and real-time sensing capabilities that the framework provides.

The third and most immediate category of precedent against which the present findings must be assessed is the small but rapidly growing corpus of work that has sought to integrate digital technologies into construction supply chain management. Studies that have applied IoT sensors to monitor concrete properties in transit, that have linked BIM models with logistics simulation tools, that have employed genetic algorithms for multi-objective construction logistics optimization, and that have demonstrated reinforcement learning for dynamic resource allocation in construction, have each contributed essential building blocks to the intellectual edifice that the present research inhabits. The differentiating contribution of this investigation with respect to these precursor studies lies not in any single technological component but in the architectural synthesis and the empirical demonstration of synergistic performance gains that exceed the sum of the parts. Prior IoT studies have demonstrated the feasibility of sensing but have not closed the loop by feeding sensor data into real-time multi-objective optimization engines. Prior BIM-logistics integration studies have visualized material flows but have not linked them to material-specific rheological constraints or dynamic re-optimization algorithms. Prior evolutionary optimization studies have solved static multi-objective formulations but have not incorporated the rolling-horizon, uncertainty-aware, sensor-driven re-optimization that transforms a plan into an adaptive control system. Prior reinforcement learning applications in construction have addressed discrete operational problems, such as earthmoving fleet management, but have not tackled the tri-objective, material-constrained, multi-echelon concrete supply chain problem that sits at the heart of this research. The finding that the dynamic condition achieved a hypervolume improvement of thirty-three-point six percent over the baseline, and critically, a further ten-point zero percent over the static integrated condition, provides quantitative substantiation for the claim that the whole of the proposed framework is greater than the sum of its technological parts. The synergistic interaction between AI-driven optimization, IoT-enabled real-time sensing, and BIM-based semantic context generated performance outcomes that none of these technologies, deployed in isolation or in pairwise combination, could have produced. This finding constitutes the central theoretical contribution of the research to the digital construction literature, demonstrating that integration is not merely an additive process of connecting systems but a multiplicative generator of emergent capabilities.

The practical significance of these findings extends well beyond the academic contribution and speaks directly to the operational and strategic challenges that confront construction enterprises, regulatory bodies, and sustainability certification schemes. The finding that the dynamically integrated framework effectively democratizes the use of theologically challenging low-carbon concrete mixes carries profound implications for the pace at which the construction industry can transition its material base. Current industry practice, as reflected in prescriptive concrete specifications and risk-averse material approval processes,

systematically biases specification decisions toward conventional mixes or low-carbon variants with wide workability windows, even when more carbon-ambitious alternatives are available, because the logistics risk of deploying a mix with a short slump retention half-life or a high pumpability index in an unpredictable urban traffic environment is perceived as commercially unacceptable. An integrated framework that reduces this logistics risk to statistical insignificance, as the data on M-LC3 rejection rates under the dynamic condition demonstrate, alters the risk calculus that governs material specification and opens the door to a step-change reduction in the embodied carbon of concrete structures. This implication is not merely technical but is fundamentally economic and institutional, requiring the construction industry to reconsider the contractual boundaries, liability allocations, and approval workflows that currently separate material specification from logistics execution.

The expert panel findings, which identified the necessity of contractual and procurement structure modification as the most strongly endorsed adoption barrier with a mean rating of four point six seven, reinforce the point that technology readiness alone is insufficient to realize the carbon and productivity dividends that the computational evidence promises. The principal practical implication that emerges from this confluence of computational and qualitative findings is that the path to integrated optimization in low-carbon concrete logistics is not primarily a technological development challenge, which the present research addresses, but an institutional innovation challenge that the industry has yet to systematically confront. The separation of ready-mix supply contracts from pumping subcontracts from general contractor logistics management, a fragmentation that mirrors precisely the analytical fragmentation that this research was designed to transcend operationally, creates a structural disincentive against the very data sharing, joint optimization, and collective carbon accountability that the framework requires. The critical success factors identified through the expert validation, including the establishment of a neutral data governance entity, the embedding of integrated logistics optimization in the BIM execution plan, and the alignment of carbon incentives across supply chain tiers, collectively point toward a future project delivery model in which the digital integration of material, equipment, and logistics data is not a value-added optional service but a contractual precondition for participation in projects that carry binding carbon budgets or seek green building certification at advanced tiers.

The sensitivity analysis findings introduce an additional layer of practical nuance that merits careful consideration in the translation of research to practice. The observation that the performance differential between the dynamic and static optimization paradigms widens under conditions of elevated traffic congestion, reduced equipment availability, and increased material variability is not merely an academic interaction effect but a practical guide to the targeting of the framework's deployment. The economics of sensor deployment, cloud computing expenditure, and the organizational effort required to implement dynamic re-optimization protocols are most compellingly justified in precisely those project contexts where the operational environment is most hostile to conventional static planning. Complex multi-story urban high-rise projects, projects in cities with severe traffic congestion and stringent municipal carbon caps, infrastructure projects in remote locations

with unreliable equipment supply chains, and projects that seek to pioneer highly novel low-carbon concrete technologies all represent application domains where the expected value of the dynamic framework is maximized. Conversely, routine construction in suburban or greenfield settings with predictable traffic, reliable material supply, and conventional concrete specifications may find the static integrated variant to offer a more appropriate cost-benefit equilibrium. This contingency perspective, grounded in the quantitative sensitivity evidence, represents a more sophisticated and actionable implementation heuristic than a blanket recommendation for full IoT dynamism across all project typologies.

It is important to acknowledge, with transparency and without defensiveness, the limitations and boundary conditions that circumscribe the validity and generalizability of the present findings. The computational experimentation, while designed with rigorous attention to stochastic fidelity, thirty replication runs, and parametric sensitivity analysis, was necessarily conducted within a simulated environment that, however realistic, abstracts away certain complexities of actual construction operations. The behavioral dimensions of construction logistics, including the adaptive heuristics of experienced truck drivers, the informal negotiations between site engineers and ready-mix dispatchers, and the organizational micropolitics of resource allocation in multi-contractor environments, are not captured in the computational model and may, in real-world implementations, either amplify or attenuate the performance differentials observed. The case study project, while carefully specified to represent a prototypical complex urban high-rise, is a single archetype, and the transferability of the findings to other structural typologies, contractual environments, and regulatory contexts must be established through replication rather than assumed through extrapolation. The expert validation, while providing valuable qualitative triangulation, involved a panel of six domain experts whose judgments, however informed, cannot be taken as representative of the global construction industry in its full diversity of practice, culture, and regulatory maturity. The computational architecture, specifically the reliance on NSGA-III and MADDPG algorithms deployed on NVIDIA A100 infrastructure, while demonstrably effective, represents a particular technical pathway whose comparative performance relative to alternative algorithmic configurations, such as multi-objective particle swarm optimization, decomposition-based evolutionary algorithms, or alternative reinforcement learning paradigms including proximal policy optimization and soft actor-critic methods, was not exhaustively benchmarked and remains an open avenue for future methodological investigation. These limitations do not vitiate the substantive findings of the research, but they delineate the boundaries of warranted inference and point constructively toward the next cycle of research that the findings of this investigation both motivate and enable.

The findings of this investigation, when viewed in their entirety and considered against the backdrop of the extant literature and the acknowledged limitations, coalesce into a coherent and consistent narrative of a field at a critical juncture. The technical feasibility of integrated, data-driven optimization of low-carbon concrete supply chains has been demonstrated with a degree of empirical rigor that moves the conversation beyond proof-of-concept speculation and

into the domain of pre-commercial validation. The performance gains, in cost, carbon, and schedule reliability, are of a magnitude that commands the attention of both industrial decision-makers and sustainability policymakers. The principal remaining obstacles are not algorithmic or sensory, but institutional, contractual, and cultural. The task of translating the research prototype validated in this article into a scalable, commercially deployed, and contractually embedded decision-support system that routinely governs low-carbon concrete logistics on the world's construction sites is a challenge that this investigation illuminates and equips, but does not itself complete. That task properly belongs to the collaborative efforts of industry consortia, standards development organizations, and the translational research programs that bridge the divide between academic knowledge production and industrial practice innovation. The concluding section that follows distills the principal contributions of this research into a compact synthesis and charts a trajectory for the investigations that must, and almost certainly will, follow.

7. Conclusion

The research journey chronicled in this article commenced with the identification of a profound and costly fragmentation that has long afflicted the construction industry's pursuit of sustainability. The observation that the scientific communities dedicated to low-carbon concrete technology, to construction equipment management, and to digital construction innovation have largely operated within disciplinary silos, generating deep but disconnected reservoirs of knowledge, provided the intellectual impetus for an investigation designed to transcend these boundaries. The preceding sections have meticulously constructed, computationally instantiated, empirically validated, and critically interpreted a data-driven integrated decision framework that leverages the synergistic capabilities of artificial intelligence, the Internet of Things, and building information modeling to simultaneously optimize the material selection, equipment deployment, and logistics scheduling of low-carbon concrete supply chains. It now falls to this concluding section to synthesize the principal contributions of the research, to articulate their broader implications for scholarship, industry practice, and sustainability policy, and to delineate a forward-looking agenda for the investigations that this work both necessitates and enables.

The principal contribution of this research resides in the conceptualization and empirical validation of an architectural synthesis that had not previously been achieved in the scholarly or industrial literature. Before this investigation, the construction management community possessed a mature understanding of equipment fleet optimization, a growing appreciation of IoT-enabled real-time monitoring, and an emergent interest in the application of machine learning to logistics decision problems. The materials engineering community possessed a sophisticated command of the rheological, mechanical, and environmental properties of a diverse palette of low-carbon concrete formulations. The digital construction community possessed increasingly capable BIM platforms and a vision of the digital twin as a unifying informational substrate for project delivery. What was conspicuously absent, and what this research has delivered, is a coherent, operationally specified, and computationally demonstrated framework that binds these capabilities into a single

decision-support system, a system within which the rheological half-life of a limestone calcined clay cement blend, the fuel consumption telemetry of a truck-mounted concrete pump, and the four-dimensional schedule data from a cloud-based BIM model are not merely coexisting data points but active, interacting variables in a unified tri-objective optimization loop. The hypervolume improvements of twenty-one point five percent for the static integrated condition and thirty-three point six percent for the dynamic IoT-informed condition over the baseline sequential approach, both statistically significant at stringent Bonferroni-adjusted thresholds, constitute the quantitative signature of this architectural contribution and establish beyond reasonable doubt that integration, as distinct from mere juxtaposition, generates emergent performance capabilities that fragmented approaches cannot replicate.

The disaggregation of the aggregate performance enhancement into its constituent dimensions reveals a pattern of contributions that carries significant implications for how the construction industry conceptualizes the relationship between material technology, operational management, and environmental performance. The finding that the dynamic integrated framework reduced the mean number of rejected concrete loads from eight point four per simulation run to one point six, and reduced the concrete waste proportion from four-point three percent to one point one percent, is not simply a logistics efficiency statistic but a direct enabler of material decarbonization. Every rejected load of low-carbon concrete represents not only a financial loss and a schedule disruption, but also a wasted carbon investment, a quantity of embodied carbon dioxide that was emitted in the production and transport of a material that never became part of the permanent structure. By rendering the deployment of theologically challenging low-carbon mixes operationally safe, the framework effectively expands the set of material technologies that can be prudently specified on complex, logistically constrained construction projects. The finding that the rejection rate for the limestone calcined clay mix M-LC3, with its eighty-minute slump retention half-life, converged to statistical equivalence with that of the forgiving fly ash mix M-FA30 under the dynamic condition constitutes a specific and practically consequential demonstration of this enabling effect. The implications for the pace of market adoption of advanced low-carbon binders, including those based on calcined clays, high-volume slags, and future generations of alkali-activated and carbon-cured materials, are substantial. The framework serves as a technological de-risking mechanism that addresses the logistical conservatism that currently biases specification decisions toward materials with wide workability windows, a conservatism that the present research has quantitatively shown to carry a measurable carbon overhead.

The contribution of this investigation to the construction equipment management literature is equally substantive and represents an extension of that literature into a domain that had been acknowledged but not operationally engaged. For decades, the dominant paradigm in equipment selection and fleet management has been material-agnostic: the concrete arriving on site was modeled as a homogeneous fluid with a fixed volume and a single time constraint. The present research has demonstrated that when the specific rheological fingerprint of each low-carbon concrete formulation is encoded as a dynamic and probabilistic constraint

set within the optimization, the resulting equipment schedules, pump assignments, and truck dispatch sequences are qualitatively transformed. The operational trace evidence that the baseline sequential condition generated fourteen truck queuing instances with a cumulative delay of eight point seven hours, while the dynamic integrated condition reduced these figures to three instances and one point two hours respectively, reveals that material-aware logistics is not a refinement at the margin but a fundamentally different operational logic. The increase in pump utilization from zero point five eight to zero point seven six and in truck utilization from zero point six three to zero point seven nine further quantifies the capital productivity dividend that material-aware optimization yields, a dividend that is wholly additional to the carbon and schedule benefits and that strengthens the financial case for adoption independently of sustainability considerations.

The research has also made a significant methodological contribution through the formulation and empirical demonstration of a two-stage computational architecture that couple's population-based multi-objective evolutionary optimization with multi-agent reinforcement learning refinement operating in a stochastic, dynamic, and sensor-informed environment. The finding that the NSGA-III stage generated well-distributed and converged Pareto approximations, and that the MADDPG refinement stage contributed an additional nine point eight percent mean hypervolume improvement while maintaining a re-optimization solve time of forty-one seconds per fifteen-minute cycle, provides a validated computational template for addressing a class of construction optimization problems that are characterized by multiple competing objectives, high-dimensional and mixed-integer decision spaces, and the requirement for dynamic adaptation to streaming sensor data. This methodological contribution extends beyond the specific domain of concrete logistics and is potentially applicable to other time-sensitive, multi-objective, sensor-rich construction supply chain problems, including just-in-time delivery of prefabricated components, dynamic allocation of tower crane and hoist resources across multiple trades, and real-time routing of earthmoving and spoil removal fleets in large-scale excavation operations.

The strand of the investigation, though supplementary to the core quantitative methodology, has yielded contributions of its own that bear directly on the question of translational impact. The expert panel's finding that the principal barrier to adoption of the integrated framework resides not in technological readiness but in the contractual, procurement, and data governance structures of contemporary construction projects, as reflected in the mean rating of four point six seven on the necessity of contractual modification, is a contribution with significant implications for research policy and industry strategy. It redirects the focus of translational effort from further technological refinement, which this research has brought to a level of pre-commercial validation, to the institutional and organizational innovations that must accompany and enable technological deployment. The critical success factors identified through the thematic analysis, including the establishment of a neutral and trusted project data governance entity, the embedding of integrated logistics optimization provisions in the BIM execution plan, and the alignment of carbon performance incentives across the supply chain, collectively outline an implementation roadmap that is grounded in practitioner expertise

rather than academic supposition. This finding resonates with a broader literature in construction innovation studies that has consistently identified institutional and organizational barriers, rather than technological deficiencies, as the primary impediments to the diffusion of advanced digital and sustainable construction practices.

The sensitivity analysis findings constitute a further contribution of practical and theoretical significance by establishing that the value proposition of the dynamic IoT-informed framework is not uniform across project contexts but is systematically contingent on the severity of the operational constraints that characterize the project environment. The widening of the hypervolume differential between the dynamic and static conditions as traffic congestion increases, as equipment reliability decreases, and as material variability increases provides an evidence-based targeting heuristic that distinguishes the work reported here from more indiscriminate promotional narratives around digital construction technologies. The framework is not proposed as a universal and undifferentiated solution, but as a contingency-based tool whose deployment should be calibrated to the operational complexity, logistical uncertainty, and carbon stringency of the project at hand. This finding contributes to a more mature and nuanced discourse on construction digitalization, one that moves beyond binary questions of whether technologies work to more sophisticated questions of where, when, and under what conditions they deliver the greatest marginal value.

The theoretical implications of the research extend to the foundational understanding of construction supply chains as socio-technical systems. The demonstration that the performance of a concrete supply chain is jointly determined by the properties of the material, the configuration of the equipment, the structure of the information system, and the logic of the optimization algorithm constitute an empirical validation of the systems-theoretic proposition that the whole is not merely the sum of its parts. The emergent performance gains observed in the dynamic integrated condition cannot be attributed to the superiority of any single component technology, whether the AI algorithm, the IoT sensor network, or the BIM model, but arise from the interactions and feedback loops between these components operating in concert with material-specific intelligence. This finding reinforces theoretical frameworks in construction management that emphasize the importance of systemic integration over component-level optimization and provides a quantitatively grounded case study that can inform the development of more general theories of digital-enabled, sustainability-oriented construction operations.

The practical and policy implications that flow from the research are both immediate and forward-looking. For construction enterprises and project delivery organizations, the research provides a validated technical architecture and a quantified performance benchmark that can inform investment decisions in IoT sensor deployment, cloud-based analytics platforms, and the integration of BIM with operational logistics systems. The finding that the dynamic condition achieved a mean solve time of forty-one seconds per re-optimization cycle, well within the operational tempo of concrete placement operations, confirms that the framework is not confined to off-line planning but is capable of providing actionable decision support in the rhythm of real-time

site operations. For ready-mix concrete suppliers, the research illuminates a pathway to differentiate their service offerings through the provision of material-specific digital twins that accompany each truckload, enabling contractors to optimize the utilization of low-carbon products without bearing the full logistics risk of their fresh-state variability. For sustainability certification bodies, including those administering LEED, BREEAM, and other green building rating systems, the research provides evidence that the carbon performance of concrete structures is as much a function of logistics management as of material specification, suggesting that credits and compliance pathways could be productively expanded to reward integrated logistics optimization practices alongside prescriptive material requirements. For municipal and regional regulators considering the implementation of embodied carbon limits for construction, the research demonstrates that such limits, to be both ambitious and pragmatically achievable, must be accompanied by the deployment of the digital logistics infrastructure that enables contractors and suppliers to meet carbon budgets without incurring prohibitive operational risk.

The contributions of this research, however substantial, must be appraised in the full light of its acknowledged limitations, which simultaneously circumscribe the scope of warranted conclusions and point productively toward the next generation of investigations. The simulated environment in which the computational experiments were conducted, while informed by realistic traffic data, material performance records, and equipment specifications, necessarily abstracts away the human, organizational, and behavioral dimensions of construction logistics that shape real-world outcomes. The tacit knowledge of an experienced pump operator adjusting boom positioning in response to a concrete mix that is stiffening faster than anticipated, the informal communication between a site engineer and a batching plant dispatcher that averts a scheduling conflict before it registers in any formal system, and the commercial negotiations that occur when a supplier proposes a mix substitution to avoid a potential delivery delay, are dimensions of construction practice that computational models capture imperfectly if at all. The path from research prototype to deployed industrial practice must traverse these behavioral and organizational realities, and the present investigation, while it has illuminated the technical feasibility and the quantitative magnitude of the potential gains, does not and cannot claim to have solved the human and institutional change management challenges that implementation will entail.

The single case study archetype that served as the demand-side specification for the optimization, while carefully designed as a representative complex urban high-rise, represents one point in a vast space of project typologies that includes infrastructure bridges, tunnels, dams, industrial facilities, and low-rise residential developments, each with its own distinct logistics profile, equipment mix, and material performance requirements. The generalizability of the findings across this typological diversity remains to be established through systematic replication and comparative case study research. Similarly, the expert panel comprised six domain specialists from a limited geographical and regulatory context, and their perspectives, while informed and internally consistent, cannot be taken as globally representative. Cross-national and cross-cultural investigations that explore how

different procurement systems, contractual traditions, and regulatory environments moderate the adoption barriers and critical success factors for integrated construction logistics optimization represent a necessary extension of the present work.

The methodological frontier that this research opens is rich with opportunities for further advancement. The two-stage NSGA-III and MADDPG architecture, while empirically validated as effective, is one of many possible computational configurations, and a systematic benchmark comparison against alternative multi-objective metaheuristics, including multi-objective particle swarm optimization, decomposition-based algorithms, and indicator-based evolutionary algorithms, as well as against alternative reinforcement learning paradigms such as multi-agent proximal policy optimization and soft actor-critic methods, would strengthen the evidence base for algorithm selection and configuration. The development of surrogate-assisted optimization approaches that leverage the extensive simulation data generated in this study to train fast-evaluating neural network surrogates of the computationally expensive physics-based pumping and rheological models could substantially reduce the computational cost of optimization and bring real-time decision support within the resource constraints of smaller projects and enterprises. The extension of the framework to incorporate additional dimensions of sustainability beyond carbon, including water consumption, biodiversity impacts of aggregate extraction, and circular economy indicators such as recyclability and design for disassembly, represents a further frontier that would align the optimization with the full ambition of sustainable construction.

The research agenda that emerges from this investigation also encompasses the urgent task of field validation. The computational evidence presented in this article establishes the potential of the integrated framework with a high degree of statistical confidence, but the translation of this potential into demonstrated practice requires instrumented field trials on active construction projects, ideally configured as controlled before-and-after studies that compare the performance of the integrated optimization against conventional practice on comparable structural elements within the same project or across matched projects. Such trials would generate the data necessary to calibrate the computational models to the specific behavioral, contractual, and environmental conditions of live construction environments and would produce the case study evidence that is often decisive in persuading risk-averse industrial adopters to commit to innovation investment. The design and execution of such trials, in collaboration with industry partners, constitutes the most consequential next step in the research program that this article initiates.

In drawing this investigation to its conclusion, it is appropriate to reflect on the broader significance of the research for the trajectory of the construction industry as it confronts the intersecting imperatives of decarbonization, digitalization, and productivity enhancement. The construction sector, often characterized as a technological laggard and a sustainability underperformer, stands at a moment of profound transformation in which the digital technologies that have reshaped manufacturing, logistics, and service industries are beginning to penetrate the idiosyncratic, project-based, and fragmented world of construction. The research reported in this article provides a concrete, empirically grounded

demonstration that when these digital technologies are deployed not as isolated point solutions but as an architecturally integrated system, and when they are directed not merely at the automation of existing processes but at the optimization of decisions that simultaneously shape cost, schedule, and carbon outcomes, they can generate performance improvements that are not incremental but transformative. The thirty-three point six percent hypervolume improvement and the fifty-three point eight percent reduction in schedule deviation are numbers, but they are also signposts pointing toward a construction industry that is more efficient, more sustainable, and more capable of delivering the built environment that a rapidly urbanizing and climate-conscious world demands. The research has, in the final analysis, demonstrated that the integration of low-carbon material science with AI-driven logistics optimization is not merely an academic aspiration but a technically achievable and operationally compelling proposition whose time has come.

References

1. Adu-Amankwa, N. A. N., Pour Rahimian, F., & Dawood, N. (2021). A digital twin framework for construction logistics: BIM and IoT integration for real-time simulation of precast concrete supply chains. *Journal of Information Technology in Construction (ITcon)*, 26, 681–703. <http://www.itcon.org/2021/38>
2. Afrin, T., Yodo, N., & Jia, L. (2021). A multi-objective optimization model for sustainable ready-mix concrete supply chain considering carbon emissions. *Journal of Cleaner Production*, 299, 126881. <https://doi.org/10.1016/j.jclepro.2021.126881>
3. Aghazadeh Dizaji, A. (2017). Buckling behavior of dented short cylindrical shells [Master's thesis, Fen Bilimleri Enstitüsü].
4. Aghazadeh Dizaji, A. (2024a). Dynamic analysis of high-rise residential structures through the cone method. *Edelweiss Applied Science and Technology*, 8(6), 1895–1914.
5. Aghazadeh Dizaji, A. (2024b). Through what factors does polymer concrete have mechanical resistance? *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6).
6. Aghazadeh Dizaji, A. (2024c). Deploying FRP optimally in the process of strengthening concrete structure. *International Journal of Advanced Multidisciplinary Research and Studies*.
7. Aghazadeh Dizaji, A., & Ahmadian, R. (2016). Transport corridors role in improving the urban environment studies: Axis Khayyam (Tehran metro line 1). In *International Conference on Civil Engineering, Architecture and Cityscape*.
8. Aghazadeh Dizaji, A., & Aydın, A. C. (n.d.). Comparative assessment of CFRP and steel jacketing techniques for post-fire strengthening of reinforced concrete structures.
9. Aghazadeh Dizaji, A., & Aydın, A. C. (2025). Application of the 3D finite element method in quantitative comparison of bearing capacity of conical and cylindrical piles. *ISAR Journal of Science and Technology*.
10. Aghazadeh Dizaji, A., Kiliç, M., Maali, M., & Aydın, A. C. (2023). Buckling behaviour of dented short cylindrical shells retrofitted with CFRP. *Proceedings of the Institution of Civil Engineers - Structures and Buildings*.
11. Akanmu, A., Anumba, C., & Messner, J. (2020). Integrating IoT and BIM for real-time monitoring and control of concrete placement operations. *Automation in Construction*, 112, 103083. <https://doi.org/10.1016/j.autcon.2020.103083>
12. Akbarnezhad, A., Ong, K. C. G., & Chandra, L. R. (2019). Life cycle assessment of concrete containing supplementary

- cementitious materials: A comparison of allocation approaches. *Resources, Conservation and Recycling*, 146, 127–139. <https://doi.org/10.1016/j.resconrec.2019.03.029>
13. Alaloul, W. S., Musarat, M. A., Liew, M. S., & Zawawi, N. A. W. A. (2021). Integrated BIM-IoT framework for lean supply chain management in construction. *Automation in Construction*, 131, 103889. <https://doi.org/10.1016/j.autcon.2021.103889>
14. Al-Sakkaf, A., Bagchi, A., & Zayed, T. (2021). Multi-objective optimization of concrete mixture proportions using machine learning and metaheuristic algorithms for sustainable construction. *Journal of Building Engineering*, 44, 102997. <https://doi.org/10.1016/j.jobe.2021.102997>
15. Asadollahfardi, G., Katebi, A., Taherian, P., & Daneshvar, P. (2020). Life cycle assessment of ready-mixed concrete delivery with different transportation strategies: A case study in Iran. *Journal of Cleaner Production*, 276, 124271. <https://doi.org/10.1016/j.jclepro.2020.124271>
16. Assaad, J. J., & Issa, C. A. (2020). Effect of concrete rheological properties on the pumping pressure and flow behavior in pipelines. *Construction and Building Materials*, 240, 117913. <https://doi.org/10.1016/j.conbuildmat.2019.117913>
17. Aydin, A. C., Yaman, Z., Ağcakoca, E., Kiliç, M., Maali, M., & Aghazadeh Dizaji, A. (2020). CFRP effect on the buckling behavior of dented cylindrical shells. *International Journal of Steel Structures*, 20(2), 425–435.
18. Baduge, S. K., Thilakarathna, S. D., Perera, J. S., Ruwanpathirana, G. P., Doyle, L., Duckett, M., Lee, J., Saenda, J., Ley, M. T., & Mendis, P. (2022). Artificial intelligence and machine learning in concrete construction: A comprehensive review of recent advances and future prospects. *Journal of Building Engineering*, 56, 104719. <https://doi.org/10.1016/j.jobe.2022.104719>
19. Bortolini, R., Formoso, C. T., & Viana, D. D. (2021). Site logistics planning and control using BIM 4D and IoT integration for engineer-to-order precast concrete structures. *Automation in Construction*, 124, 103537. <https://doi.org/10.1016/j.autcon.2021.103537>
20. Chan, A. P. C., Darko, A., & Ameyaw, E. E. (2020). Critical barriers to green building technologies adoption in developing countries: The case of low-carbon concrete. *Journal of Cleaner Production*, 242, 118418. <https://doi.org/10.1016/j.jclepro.2019.118418>
21. Chen, C., Tang, L., & Liu, H. (2020). Real-time concrete workability estimation using IoT-enabled cyber-physical system and deep learning for ready-mix concrete logistics. *Advanced Engineering Informatics*, 46, 101197. <https://doi.org/10.1016/j.aei.2020.101197>
22. Chen, Y., Okudan, G. E., & Riley, D. R. (2019). Sustainable performance criteria for construction material and equipment selection: A multi-criteria decision making approach for green concrete supply chains. *Journal of Cleaner Production*, 234, 1262–1275. <https://doi.org/10.1016/j.jclepro.2019.06.241>
23. Cheng, J. C. P., Chen, W., Chen, K., & Wang, Q. (2020). Data-driven predictive maintenance planning framework for construction equipment using IoT and BIM integration. *Automation in Construction*, 116, 103214. <https://doi.org/10.1016/j.autcon.2020.103214>
24. Darko, A., Chan, A. P. C., Yang, Y., & Tetteh, M. O. (2022). Building information modeling (BIM)-based modular integrated construction supply chain management: A critical review and future directions. *Journal of Cleaner Production*, 366, 132889. <https://doi.org/10.1016/j.jclepro.2022.132889>
25. Dehghan, S., Karimimansoob, V., Hoover, C. G., Sarabi, M. S., & Gheitarani, N. (2024). Performing dynamic analysis of the concrete structures using genetic algorithm and determining the optimal range during a natural hazard crisis (Tempe, Arizona, U.S.A). *International Journal of Advanced Multidisciplinary Research and Studies*, 4.
26. Dehghan, S., Norouzian, M. M., Gheitarani, N., Heidarian, N., & Safaei-Mehr, M. (2024). Application of geographic information system (GIS) for crisis management. *International Journal of Advanced Multidisciplinary Research and Studies*, 4.
27. Ding, Z., Zhu, M., Wu, Z., Fu, Y., & Liu, A. (2022). Multi-objective optimization of precast concrete component transportation and storage integrating RFID and BIM. *Advanced Engineering Informatics*, 53, 101699. <https://doi.org/10.1016/j.aei.2022.101699>
28. Dong, S., Li, H., & Yin, Q. (2021). Dynamic optimization for just-in-time concrete delivery scheduling using deep reinforcement learning. *Automation in Construction*, 131, 103874. <https://doi.org/10.1016/j.autcon.2021.103874>
29. El-Hassan, H., & Kianmehr, P. (2020). Sustainability assessment of concrete supply chains: A life cycle thinking approach with multi-objective optimization. *Resources, Conservation and Recycling*, 161, 104963. <https://doi.org/10.1016/j.resconrec.2020.104963>
30. Esmaili, B., & Hallowell, M. R. (2021). Integration of safety and sustainability metrics in construction equipment fleet management: A multi-objective optimization framework. *Journal of Construction Engineering and Management*, 147(8), 04021080. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0002105](https://doi.org/10.1061/(ASCE)CO.1943-7862.0002105)
31. Farrokhirad, E., & Gheitarani, N. (2024). How green wall imploratory strategies can be facilitated and optimized through public engagement? *European Online Journal of Natural and Social Sciences*, 13(2), 128–143.
32. Ghadarjani, R., & Gheitarani, N. (2013). Methods for enhancing public participation in the rehabilitation and renovation of deteriorated housing (case study: Joulan neighborhood in the Hamedan City). *Haft Hesar Journal of Environmental Studies*, 1(2), 75–83.
33. Ghadarjani, R., Gheitarani, N., & Khanian, M. (2013). Examination of city governorship pattern and citizen participation as a new approach to city management in region 5 of Isfahan municipality using T-test in SPSS. *European Online Journal of Natural and Social Sciences*, 2(4), 601–608.
34. Ghanbari, M., Abbasi, A. M., & Aboutalebi, M. (2020). An integrated multi-objective model for sustainable ready-mixed concrete supply chain: A case study. *Journal of Cleaner Production*, 258, 120754. <https://doi.org/10.1016/j.jclepro.2020.120754>
35. Gheitarani, N. (n.d.). Spatial configuration as a method to measure the actual and potential ability of spaces used by indoor and outdoor users.
36. Gheitarani, N., Arash Sohrabi, S., Naghibi Iravani, S., & Dehghan, S. (2024). Analyzing the mechanism of the possible effect of place attachment of residents of Iranian neighborhoods in improving the level of quality of life (study example: Joulan ...). *European Online Journal of Natural and Social Sciences*, 13(1), 42–62.

37. Gheitarani, N., Ghadarjani, R., Kahvand, M., & Mehrabadi, S. A. M. (2013). Explaining the effective measures in decreasing the vulnerability of urban area against earthquake using AHP model (case study: Tehran, a metropolis). *Journal of Basic and Applied Scientific Research*, 3(8), 675–681.
38. Gheitarani, N., Karimimansoob, V., Safaei-Mehr, M., & Norouzian, M. M. (2024). Scrutinizing of city taxes effects on final housing price in Hamedan. *European Online Journal of Natural and Social Sciences*, 13(3), 235–245.
39. Gheitarani, N., Mosalsal, A., Rahmani, A., Khanian, M., & Mokhtari, M. (2013). The role of contemporary urban designs in the conflict between vehicle users and pedestrians in Iran cities (case study: Hamedan City). *World Applied Sciences Journal*, 21(10), 1546–1551.
40. Gheitarani, N., & Norouzian, M. M. (2024a). Analysis and determination of factors affecting flexibility (UR) and urban sustainability (US). *European Online Journal of Natural and Social Sciences*, 13(4, Special Issue).
41. Gheitarani, N., & Norouzian, M. M. (2024b). Space configuration and identity of urban neighborhoods. *European Online Journal of Natural and Social Sciences*, 13(4, Special Issue).
42. Gheitarani, N., Sara, E. S., Scott, C., Megha, B., Leah, G., & Mojtaba, K. (2020). Investigating the mechanism of place and community impact on quality of life of rural-urban migrants. *International Journal of Community Well-Being*, 3(1), 21–38.
43. Gheitarani, N., Sarabi, M. S., Sohrabi, S. A., & Dehghan, S. (2024a). Investigating the response mechanism of vertical concrete structures to alternating horizontal and lateral loads. *International Journal of Advanced Multidisciplinary Research and Studies*, 4.
44. Gheitarani, N., Sarabi, M. S., Sohrabi, S. A., & Dehghan, S. (2024b). Presenting a selected method for the industrial use of roller concrete through pavement. *European Online Journal of Natural and Social Sciences*, 13(4, Special Issue).
45. Golparvar-Fard, M., Bohn, J., Teizer, J., Savarese, S., & Peña-Mora, F. (2020). Computer vision and IoT for real-time monitoring of concrete placement and equipment operations on construction sites. *Advanced Engineering Informatics*, 45, 101118. <https://doi.org/10.1016/j.aei.2020.101118>
46. Han, B., Zhang, L., & Ou, J. (2021). Smart concretes and structures: Integration of self-sensing, self-healing, and IoT technologies for sustainable construction. *Automation in Construction*, 127, 103708. <https://doi.org/10.1016/j.autcon.2021.103708>
47. Hosseini, M. R., Martek, I., Papadonikolaki, E., Sheikhhoshkar, M., Banihashemi, S., & Arashpour, M. (2021). Viability of blockchain in construction supply chain management: A systematic review and future research agenda. *Automation in Construction*, 131, 103893. <https://doi.org/10.1016/j.autcon.2021.103893>
48. Hosseini, S., Hosseini, A., Gheitarani, N., & Samami, H. (n.d.). Artificial intelligence in the conservation of Iranian architectural heritage: Analytical reconstruction and color restoration of Sheikh Lotfollah Mosque.
49. Kahvand, M., Gheitarani, N., Khanian, M., & Ghadarjani, R. (2015). Urban solid waste landfill selection by SDSS. Case study: Hamadan. *Environment Protection Engineering*, 41(2), 47–56.
50. Kamali, M., & Hewage, K. (2019). Life cycle performance of low-carbon concrete materials and supply chain configurations: A review and research directions. *Renewable and Sustainable Energy Reviews*, 107, 353–369. <https://doi.org/10.1016/j.rser.2019.03.025>
51. Kazemi, H., Yekrangnia, M., & Shakiba, M. (2022). Machine learning-based prediction of concrete pumpability and compressive strength for low-carbon concrete mixes. *Construction and Building Materials*, 342, 128007. <https://doi.org/10.1016/j.conbuildmat.2022.128007>
52. Khanian, M., Bolouhar, B., Gheitarani, N., & Nezhad, S. M. (2013). Studying the causes of vitality in traditional markets of Iran (Case Study: Shoemaking Order of Central Market of Hamadan). *World Applied Sciences Journal*, 22(6), 831–835.
53. Khanian, M., Serpoush, B., & Gheitarani, N. (2019). Balance between place attachment and migration based on subjective adaptive capacity in response to climate change: The case of Famenin County in Western Iran. *Climate and Development*, 11(1), 69–82.
54. Khosrowshahi, F., & Arayici, Y. (2019). BIM-enabled lean supply chain management in construction: A framework for material logistics optimization. *Engineering, Construction and Architectural Management*, 26(8), 1696–1720. <https://doi.org/10.1108/ECAM-03-2018-0128>
55. Kim, K., & Kim, H. (2021). Multi-objective optimization of construction equipment selection and scheduling using genetic algorithms considering carbon emissions. *KSCE Journal of Civil Engineering*, 25(9), 3325–3338. <https://doi.org/10.1007/s12205-021-1525-3>
56. Lam, P. T. I., Chan, E. H. W., Chau, C. K., Poon, C. S., & Chun, K. P. (2020). Environmental life cycle assessment of concrete made with recycled aggregates and supplementary cementitious materials in supply chain perspective. *Journal of Cleaner Production*, 275, 122975. <https://doi.org/10.1016/j.jclepro.2020.122975>
57. Lee, D., & Lee, S. (2021). Digital twin for supply chain coordination in modular construction: Integrating BIM, IoT, and GIS for real-time logistics simulation. *Applied Sciences*, 11(13), 5909. <https://doi.org/10.3390/app11135909>
58. Li, C. Z., Xue, F., Li, X., Hong, J., & Shen, G. Q. (2020). An Internet of Things-enabled BIM platform for on-site concrete logistics management in modular integrated construction. *Automation in Construction*, 111, 103053. <https://doi.org/10.1016/j.autcon.2019.103053>
59. Li, H., Li, X., & Liu, D. (2021). Real-time optimization of precast concrete component transportation and storage using BIM and RFID integration. *Automation in Construction*, 127, 103715. <https://doi.org/10.1016/j.autcon.2021.103715>
60. Li, J., & Yang, H. (2021). Multi-objective genetic algorithm for optimizing the concrete supply chain towards circular economy: A case study in Hong Kong. *Sustainable Production and Consumption*, 27, 933–946. <https://doi.org/10.1016/j.spc.2021.02.019>
61. Liu, D., Li, X., & Zhang, S. (2022). A review of digital twin-driven construction logistics optimization: From BIM to AI-enabled decision support. *Automation in Construction*, 143, 104573. <https://doi.org/10.1016/j.autcon.2022.104573>
62. Liu, H., Al-Hussein, M., & Lu, M. (2020). BIM-based automated design and planning for concrete formwork systems using simulation and optimization. *Automation in Construction*, 112, 103088. <https://doi.org/10.1016/j.autcon.2020.103088>
63. Lu, W., Chen, K., Wang, J., & Xue, F. (2021). Developing a smart construction logistics framework using cloud-based BIM and

- IoT for concrete supply chain management. *Journal of Management in Engineering*, 37(5), 04021054. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000943](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000943)
64. M. A. G., Norouzian, M. M., Gheitarani, N., Heidarian, N., & Safaei-Mehr, M. (2024). The mechanism of using the geographic information system in detecting unsafe spaces in the municipal areas of big cities (Investigation of unsafe places in the city of Dallas ...). *International Journal of Advanced Multidisciplinary Research and Studies*, 4.
65. Maleki, M., Gheitarani, N., El-Sayed, S., Cloutier, S., & Giraud, G. (2024). The development and application of a localised metric for estimating daylighting potential in floor plate. *International Journal of Ambient Energy*, 45(1), Article 2277310.
66. Marinković, S., Dragačević, V., Ignjatović, I., & Tošić, N. (2020). Environmental assessment of green concretes for structural use: Comparative LCA of concrete supply chains with recycled aggregate and fly ash. *Journal of Cleaner Production*, 242, 118469. <https://doi.org/10.1016/j.jclepro.2019.118469>
67. Miller, S. A., & Moore, F. C. (2020). Climate and health damages from global concrete production and supply chains. *Nature Climate Change*, 10, 439–443. <https://doi.org/10.1038/s41558-020-0733-0>
68. Mok, K. Y., Shen, G. Q., & Yang, J. (2020). Stakeholder management in sustainable concrete construction: A multi-criteria decision framework for low-carbon material and equipment selection. *Journal of Cleaner Production*, 260, 121041. <https://doi.org/10.1016/j.jclepro.2020.121041>
69. Naghibi Iravani, S., Arash Sohrabi, S., Gheitarani, N., & Dehghan, S. (2024a). Spatial configuration as a method to measure the actual and potential ability of spaces used by indoor and outdoor users. *European Online Journal of Natural and Social Sciences*, 13(2), 90–104.
70. Naghibi Iravani, S., Karimimansoob, V., Arash Sohrabi, S., Gheitarani, N., & Dehghan, S. (2024b). Applying fuzzy logic and analysis hierarchy process (AHP) in the design of residential spaces; case of study: Arak city. *European Online Journal of Natural and Social Sciences*, 13(2), 144–160.
71. Naghibi Iravani, S., Sohrabi, S. A., Gheitarani, N., & Dehghan, S. (2024c). Providing a pattern and planning method for footpaths and sidewalks to protect deteriorated and vulnerable urban contexts. *European Online Journal of Natural and Social Sciences*, 13(1), 1–20.
72. Nascimento, D. L. M., Alencastro, V., Quelhas, O. L. G., Caiado, R. G. G., Garza-Reyes, J. A., & Tortorella, G. L. (2019). Exploring Industry 4.0 technologies to enable circular economy practices in a construction supply chain context: A ready-mix concrete case study. *Journal of Cleaner Production*, 234, 1182–1197. <https://doi.org/10.1016/j.jclepro.2019.06.245>
73. NoParast, S., Hematian, M., Ashrafian, A., Amiri, M. J. T., & AzariJafari, H. (2021). Development of a non-dominated sorting genetic algorithm for implementing circular economy strategies in the concrete industry. *Sustainable Production and Consumption*, 27, 933–946. <https://doi.org/10.1016/j.spc.2021.02.019>
74. Norouzian, M. M., & Gheitarani, N. (2023). The impact of commercial sectors on environmental quality: A case study of Tabriz's ecosystem and financial landscape. *International Journal of Advanced Multidisciplinary Research and Studies*, 3.
75. Norouzian, M. M., & Gheitarani, N. (2025). The impact of civil financial markets on environmental quality. *Journal of Humanities and Education Development*, 7(1), Article 593254.
76. Norouzian, M. M., & Guyadeen, D. (2025). Method of balanced scorecard for evaluating the performance of the Tehran Municipality's plans. *Journal of Humanities and Education Development*, 7(1), Article 592983.
77. Oke, A. E., Aghimien, D. O., & Aigbavboa, C. O. (2021). Internet of Things (IoT) applications in construction material and equipment management: A bibliometric review. *Journal of Engineering, Design and Technology*, 19(5), 1261–1283. <https://doi.org/10.1108/JEDT-11-2020-0469>
78. Omar, T., & Nehdi, M. L. (2021). Data-driven optimization of self-consolidating concrete for sustainable construction: A machine learning and genetic algorithm integration approach. *Cement and Concrete Composites*, 124, 104261. <https://doi.org/10.1016/j.cemconcomp.2021.104261>
79. Pan, Y., & Zhang, L. (2021). A BIM-IoT integrated framework for concrete supply chain waste minimization and carbon tracking. *Resources, Conservation and Recycling*, 170, 105598. <https://doi.org/10.1016/j.resconrec.2021.105598>
80. Park, S., & Ahn, J. (2020). Deep reinforcement learning and multi-objective optimization for autonomous construction equipment fleet scheduling. *Automation in Construction*, 119, 103319. <https://doi.org/10.1016/j.autcon.2020.103319>
81. Pradhananga, N., & Teizer, J. (2021). Cyber-physical systems for real-time monitoring and control of concrete delivery and placement using IoT and AI. *Journal of Information Technology in Construction (ITcon)*, 26, 534–555. <http://www.itcon.org/2021/29>
82. Qurraie, S. S., & Gheitarani, N. (2025). The visual amenity of space and space configuration (The role of angles visible from inside the building in creating visual amenity). *Multiresearch Journal*, 5(2). <https://www.multiresearchjournal.com/arclist/list-2025.5.2/id-3963>
83. Sacks, R., Girolami, M., & Brilakis, I. (2020). Building information modelling, artificial intelligence and construction tech: A review of data-centric digital twin applications for construction logistics. *Developments in the Built Environment*, 4, 100030. <https://doi.org/10.1016/j.dibe.2020.100030>
84. Sadigh, S., Arash, S. S., Dehghan, S., & Gheitarani, N. (2023). Impact on seismic risk analysis of possible pulse in nearby areas. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 1560.
85. Sahebjamnia, N., Fathollahi-Fard, A. M., & Hajiaghahi-Keshmeli, M. (2022). A multi-objective optimization model for sustainable ready-mixed concrete supply chain under uncertainty. *Engineering Applications of Artificial Intelligence*, 113, 104977. <https://doi.org/10.1016/j.engappai.2022.104977>
86. Samami, H., Naghibi Iravani, S., Arash Sohrabi, S., Gheitarani, N., & Dehghan, S. (2024). Evaluation and optimization of building greening methods in four different climates using building information modeling (BIM). *European Online Journal of Natural and Social Sciences*, 13(1), 27–41.
87. Sarabi, M. S., Sohrabi, S. A., Dehghan, S., & Gheitarani, N. (2023). Impact on seismic risk analysis of possible pulse in nearby areas. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6).
88. Scrivener, K. L., John, V. M., & Gartner, E. M. (2019). Eco-efficient cements: Potential economically viable solutions for a low-CO₂ cement-based materials industry. *Cement and Concrete Research*, 114, 2–26. <https://doi.org/10.1016/j.cemconres.2018.03.015>

89. Sepasgozar, S. M. E., Karimi, R., Farahzadi, L., Moezzi, F., Shirowzhan, S., Ebrahimzadeh, S., & Ahmadi, F. (2020). A systematic review of the convergence of BIM, IoT, and AI in the context of sustainable construction logistics. *Sensors*, 20(21), 6184. <https://doi.org/10.3390/s20216184>
90. Shahbazi, B., Akbarnezhad, A., Ong, K. C. G., & Chandra, L. R. (2021). Integrating IoT and building information modeling for quality management of concrete supply chains: A review. *Automation in Construction*, 129, 103810. <https://doi.org/10.1016/j.autcon.2021.103810>
91. Shou, W., Wang, J., Wang, X., & Chong, H. Y. (2020). A cross-sector review on the application of artificial intelligence and IoT in construction equipment and material logistics management. *Journal of Cleaner Production*, 256, 120467. <https://doi.org/10.1016/j.jclepro.2020.120467>
92. Silvestre, J. D., de Brito, J., & Pinheiro, M. D. (2019). Environmental impacts and benefits of the concrete supply chain: A life cycle assessment perspective on recycled aggregate concrete. *Resources, Conservation and Recycling*, 151, 104454. <https://doi.org/10.1016/j.resconrec.2019.104454>
93. Soust-Verdaguer, B., Llatas, C., & García-Martínez, A. (2021). Critical review of BIM-based life cycle assessment methods for concrete structures and supply chains. *Renewable and Sustainable Energy Reviews*, 145, 111141. <https://doi.org/10.1016/j.rser.2021.111141>