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**Research Article**

# Optimization and Computational Modeling for Sustainable Construction Supply Chains: An Analytical Approach

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**Abstract:**

The construction industry, particularly in emerging economies, faces persistent challenges in managing complex supply chains while meeting sustainability targets. This study proposes an integrated analytical approach that combines Principal Component Analysis (PCA) and Mixed-Integer Linear Programming (MILP) to optimize sustainable construction supply chains. Drawing on survey responses from 487 industry professionals and supporting project records, 35 operational and sustainability-related variables were statistically analyzed. PCA reduced these variables to seven key factors such asprocurement timeliness, inventory management, transport reliability, supplier collaboration, emissions tracking, cost monitoring, and compliance—which then formed the core input parameters for the MILP model. The optimization framework was designed to minimize total cost and CO2 emissions while enhancing sustainability performance, subject to operational, capacity, and environmental constraints. Empirical application to Indian construction projects demonstrated notable gains: a 9.9% cost reduction, 11.7% decrease in emissions, 6.3% improvement in delivery time, and a 5.8-point increase in sustainability scores compared to baseline operations. Sensitivity analysis confirmed the model's robustness under variations in demand, supplier capacity, and emission limits, with computation times under 15 seconds across all scenarios. By coupling multivariate statistical preprocessing with computational optimization, this research offers both methodological innovation and practical value. The resulting decision-support framework is adaptable to diverse civil and structural engineering contexts, providing a fast, data-driven, and sustainability-focused tool for improving supply chain performance.

## 1. Introduction

The construction industry operates within one of the most intricate and fragmented supply chain environments, characterized by a large number of stakeholders, complex interdependencies, and significant uncertainty in resource availability and delivery schedules. Projects often span multiple years, involve geographically dispersed suppliers, and require precise coordination between procurement, logistics, and on-site operations. This complexity has been amplified in recent decades by global competition, fluctuating material prices, and increasingly stringent environmental regulations [5, 13]. The multi-dimensional nature of these challenges demands an integrated analytical framework that can connect statistical analysis with optimization modelling, as conceptualized in Fig. 1, which illustrates the workflow adopted in this study.

In parallel, there is growing recognition of the need to integrate sustainability principles into construction supply chain management (SCM). Beyond cost and schedule performance, project success is now increasingly measured in terms of environmental responsibility and social impact [7,17]. Sustainable construction supply chains must therefore achieve a balance between economic efficiency, environmental stewardship, and social accountability — a triad often referred to as the "triple bottom line" [6]. Achieving this balance requires decision-making frameworks capable of analyzing complex datasets, managing multiple objectives, and producing results within tight timeframes. Traditional SCM methods in construction, such as heuristic scheduling or rule-based procurement systems, are often too rigid for today's volatile operating conditions [14]. These methods typically depend heavily on managerial experience, which can limit their adaptability when unexpected disruptions occur, such as supply shortages or sudden changes in demand. Computational optimization approaches, particularly Mixed-Integer Linear Programming (MILP), provide a mathematically rigorous means to explore trade-offs between conflicting objectives — such as cost minimization, delivery time reduction, and emissions control — while respecting operational constraints [25].

However, real-world construction supply chain datasets often contain overlapping, weakly correlated, or irrelevant variables, which can inflate model complexity, increase computation time, and dilute the clarity of optimization outputs [9]. Principal Component Analysis (PCA) has been widely used to address this issue, reducing large datasets into a smaller set of statistically significant factors without losing essential information [14, 21]. By incorporating only the most influential factors into optimization models, practitioners can achieve faster computation times while ensuring that decisions are grounded in empirical evidence.

This study develops and validates an integrated PCA–MILP framework for optimizing sustainable construction supply chains in the Indian context. Data were collected from a comprehensive industry survey and project records, and PCA was applied to extract the most critical operational and sustainability factors. These were embedded directly into an MILP model to generate optimized procurement, logistics, and environmental strategies. The proposed approach aims not only to improve operational performance and sustainability outcomes but also to deliver solutions quickly enough to support near real-time decision-making in construction project environments.

## 2. Literature Review

### 2.1 Supply Chain Management in Construction

Supply chain management (SCM) in construction differs fundamentally from manufacturing due to the temporary, project-based nature of production, the high degree of customization, and the fragmented involvement of multiple independent contractors [23]. Construction supply chains often involve complex logistical flows, diverse procurement strategies, and dependencies on external environmental and policy factors [13]. In India, additional challenges include inconsistent supplier performance, inadequate infrastructure, and volatile material prices, all of which contribute to delays, cost overruns, and reduced sustainability performance [2]. The role of complexities and adaptive strategies in ensuring resilience has also been emphasized in prior work [8], highlighting the need for construction supply chains to remain robust under uncertainty. Industry 4.0 technologies also play a pivotal role in advancing environmentally sustainable supply chains, as noted by [11].

To address these issues, researchers have increasingly called for the adoption of integrated SCM frameworks that coordinate material flows, information exchange, and stakeholder collaboration across the entire project lifecycle [4, 5]. Such frameworks emphasize the alignment of procurement planning, logistics management, and environmental monitoring, enabling decision-makers to optimize the trade-offs between economic and sustainability objectives.

### 2.2 Sustainability in Construction Supply Chains

The integration of sustainability into SCM is rooted in the triple bottom line concept, which balances environmental, social, and economic performance indicators [6]. Integration frameworks for supply chain management have long been recognized as essential to achieve seamless coordination [4]. In construction, environmental sustainability involves reducing carbon emissions, improving energy efficiency, and minimizing waste generation [18]. Social sustainability focuses on labor welfare, community engagement, and equitable resource distribution [27], while economic sustainability emphasizes cost control, resource efficiency, and long-term asset value [20]. Supplier selection and order allocation remain critical, as sustainable criteria must be embedded into procurement decisions [22]. Recent advances have integrated inventory management into green supply chain optimization models, enhancing sustainability outcomes [26].

Recent literature has shown a growing interest in green construction supply chains and their operationalization through regulatory incentives, technological innovations, and performance monitoring systems [7, 1]. However, the challenge remains in integrating these sustainability indicators into day-to-day decision-making without overburdening project managers with complex data and conflicting objectives.

### 2.3 Computational Optimization in Construction SCM

Optimization methods, particularly Mixed-Integer Linear Programming (MILP), have been widely applied to solve multi-objective problems in supply chain design and scheduling [14]; [15]. In the construction sector, MILP has been used for contractor selection, material procurement scheduling, and logistics network optimization [22]. These models can incorporate constraints related to budget limits, capacity restrictions, delivery deadlines, and environmental caps, enabling decision-makers to test different operational scenarios before implementation. Recent research has applied multi-objective optimization for sustainable supply chain design under uncertainty [24], which complements the current study's PCA–MILP approach by addressing the trade-offs between cost and sustainability.

While MILP provides an exact solution approach, its computational performance is often hindered by the size and complexity of real-world datasets [25]. This has led to growing interest in data preprocessing techniques to reduce problem dimensionality before optimization.

### 2.4 Role of Factor Analysis and PCA in SCM

Principal Component Analysis (PCA) and other factor analysis techniques have been extensively used to identify the underlying structure of large datasets, enabling researchers to extract the most influential variables while removing redundancy [9, 20]. In SCM research, PCA has been applied to supplier evaluation, risk assessment, and performance benchmarking [13]. By focusing on statistically significant components, Classical multiple attribute decision-making frameworks [10] inform many of today's optimization approaches. PCA enhances model interpretability and computational efficiency without compromising the accuracy of results [19]. In this study, the number of retained components was determined based on the scree plot presented in Fig. 2, which shows the point of inflection after the seventh component, while the factor loading relationships are depicted in Fig. 3 to highlight variable clustering patterns.

Despite their proven utility, PCA and factor analysis are rarely integrated directly into optimization frameworks in the construction context. Most existing studies treat statistical analysis and optimization as separate stages, resulting in models that either oversimplify decision variables or remain computationally heavy. This gap presents an opportunity to combine the strengths of both approaches—using PCA to streamline datasets and MILP to deliver robust optimization outputs tailored to real-world constraints. Reverse logistics contributes to competitive advantage by creating new value streams [12], a principle equally relevant to construction SCM.

### 2.5 Research Gap and Contribution

While the literature on sustainable construction SCM is extensive, few studies have developed fully integrated PCA–MILP models that directly link statistically extracted factors to computational optimization parameters. Existing work either applies factor analysis for descriptive purposes or uses optimization models without a systematic variable selection process. This study addresses this gap by proposing a unified, computationally efficient framework that embeds PCA-derived factor scores into an MILP optimization model, validated through empirical data from Indian construction projects. In doing so, it advances both the methodological and practical aspects of sustainable construction supply chain optimization.

## 3. Methodology

This study adopts a two-stage methodological framework that integrates Principal Component Analysis (PCA) for statistical data reduction and Mixed-Integer Linear Programming (MILP) for computational optimization. The approach is designed to ensure that the optimization process is both statistically grounded and computationally efficient, allowing for rapid, data-driven decision-making in construction supply chain management.

### 3.1 Data Collection and Preprocessing

Data were gathered from two primary sources: (i) a structured questionnaire survey administered to 487 professionals across the Indian construction industry, including project managers, procurement officers, and logistics coordinators; and (ii) secondary project records from active and recently completed construction projects. The survey captured 35 variables representing economic, operational, environmental, and managerial performance indicators relevant to sustainable SCM. Before analysis, the dataset underwent standard preprocessing steps: missing values were addressed through mean imputation for continuous variables and mode substitution for categorical variables; all variables were standardized to z-scores to ensure comparability; and outliers were identified through Mahalanobis distance tests and removed when statistically significant.

### 3.2 Principal Component Analysis (PCA)

PCA was applied to reduce the dimensionality of the dataset and identify the most influential performance factors. Sampling adequacy was confirmed with a Kaiser–Meyer–Olkin (KMO) measure of 0.909, and Bartlett's test of sphericity was significant at $p < 0.001$, indicating suitability for factor extraction. The analysis employed a Varimax orthogonal rotation to improve interpretability, retaining factors with eigenvalues greater than one and considering loadings ≥ 0.50 as significant. The detailed results are presented in Table 2, confirming the adequacy of the dataset for factor analysis.

Seven principal components were extracted, collectively explaining 67.3% of the total variance. The scree plot in Fig. 2 visually confirms the suitability of retaining these components, and the factor loading biplot in Fig. 3 illustrates how the original variables group together under each extracted factor. The full breakdown of eigenvalues and variance contribution is reported in Table 3, while the rotated factor loadings are presented in Table 4. These components represented distinct thematic clusters: procurement timeliness, inventory management, transport reliability, supplier collaboration, emissions tracking, cost monitoring, and compliance. Factor scores for each project were calculated and normalized to serve as direct inputs for the optimization model.

### 3.3 MILP Optimization Model

The MILP model was formulated to minimize total cost and $CO_2$ emissions while maximizing sustainability performance, subject to constraints related to demand satisfaction, supplier capacity, delivery deadlines, and environmental regulations. The general structure of the model is expressed as:

The computational model is formulated as a Mixed – Integer Linear Programming (MILP) problem.

bjective Functions:

$$\min Z = w_1 . C_{tot} + w_2 . E_{tot} - w_3 . S_{Score}$$

Where,

$C_{tot}$ = Total cost (procurement + transport +holding)

$E_{tot}$ = Total $CO_2$ emissions (transport + material production)

$S_{Score}$ = Sustainability performance score (from factor analysis)

$w_1, w_2, w_3$ = weight coefficients determined via expert elicitation

Subject to constraints:

1. Demand fulfilments:

$$\sum_{j \in s}^{\cdot} x_{ij} \geq D_i, \quad \forall i \in P$$

2. Material availability:

$$x_{ij} \leq Cap_j, \forall j \in S$$

3. Project deadline:

$$\sum_{j \in s}^{\cdot} t_{ij} x_{ij} \leq T_{max},$$

4. Environmental Cap:

$$E_{tot} \leq E_{max}$$

5. Binary Decision Variables:

$y_{ij} \in \{0,1\}$ to represent supplier selection

**Constraints** ensured that:

- Each demand node was fully satisfied within the project timeline
- Supplier capacities were not exceeded
- Emission limits were adhered to in accordance with project environmental policies

The model was implemented in IBM ILOG CPLEX Optimization Studio, with default solver settings and a termination gap of 0.01%. The decision flow, data inputs, and constraint structure are summarized in Fig. 4, providing a visual overview of the optimization process. The integration of statistical analysis with mathematical optimization has been recognized as a pathway to enhance operational efficiency [16], aligning with this study's PCA–MILP framework. The integration of PCA with MILP for decision modeling has also been explored in prior work, demonstrating improved efficiency in complex optimization problems [3].

### 3.4 Model Validation and Scenario Testing

Model validation involved comparing optimization results with baseline project data for cost, emissions, delivery time, and sustainability scores. Sensitivity analysis was conducted by varying demand, supplier capacity, and emission caps by ±20% to evaluate robustness. Computation times were recorded for each scenario to assess the framework's real-time applicability.

## 4. Results and Discussions

The findings from this study demonstrate the power of combining statistical data reduction with mathematical optimization to address complex, multi-dimensional challenges in construction supply chains. The descriptive statistics of these variables are summarized in Table 1. The PCA results provided a clear statistical foundation by reducing the original 35 survey and project-related variables into seven latent components, thereby simplifying the dataset without losing explanatory power. The Kaiser–Meyer–Olkin (KMO) score of 0.909 and Bartlett's test of sphericity ($p < 0.001$) confirmed strong sampling adequacy, as shown in Table 2, validating the robustness of the factor extraction process. The scree plot in Figure 2 and eigenvalue distribution in Table 3 confirmed that the first seven factors captured the majority of variance (67.3%), indicating that the reduced set retained the essential dynamics of construction supply chain practices. The rotated component matrix (Table 4) and the factor loading biplot (Figure 3) revealed meaningful groupings such as project planning and design, procurement efficiency, inventory control, logistics reliability, and collaboration practices, alongside cross-cutting dimensions like awareness, attitudes, and compliance.Each component carries important managerial implications. For example, “Awareness and Familiarity” and “Perceptions and Attitudes” clustered together, suggesting that human-centric variables such as training, knowledge dissemination, and organizational culture directly influence operational SCM practices. Similarly, the clustering of “Project Planning & Design” with “Procurement & Sourcing” underlined the importance of early-stage decisions on cost and schedule performance. “Inventory Management” and “Transportation & Logistics” emerged as independent but interlinked clusters, indicating that while they require specialized optimization approaches, their integration is vital for flow efficiency. Finally, “Communication & Collaboration” stood as a distinct factor, underscoring its central role in bridging different nodes of the construction supply chain. These PCA-derived clusters were further quantified through the component score coefficients in Table 5, which served as critical performance weights within the optimization framework.When embedded into the MILP optimization model, these factors yielded measurable improvements across financial, environmental, and operational dimensions. Similar integrations of PCA and MILP have been applied to manufacturing scheduling [3], demonstrating the potential of hybrid frameworks. The baseline versus optimized comparison (Figure 5) revealed that total costs were reduced by 9.9%, primarily through improved supplier selection and better-aligned procurement schedules. This validates the argument by [7] that multi-criteria optimization can deliver simultaneous economic and environmental gains. $CO_2$ emissions declined by 11.7% due to optimized transportation routes and sourcing from suppliers with lower emission profiles, aligning with findings from [15] on eco-efficient supply chains. Delivery times improved by 6.3%, a gain particularly critical in the construction sector, where schedule delays can trigger cascading cost overruns and contractual penalties. Perhaps most importantly, the composite sustainability score improved by 5.8 points, demonstrating the value of embedding statistically derived sustainability factors into mathematical optimization models. Sensitivity testing further confirmed robustness (Figure 6), as the model remained stable under ±20% fluctuations in demand, supplier capacity, and emission caps, with computation times under 15 seconds—highlighting the framework’s practical feasibility for real-time decision-making.Extending beyond general performance, the model was applied to five critical domains of supply chain operations. In project planning optimization (Table 6), the model emphasized efficient allocation of limited resources and incorporation of risk costs, ensuring that project timelines were safeguarded while avoiding over-allocation. This finding highlights the tension between resource efficiency and risk exposure, suggesting that project managers need to prioritize flexible resource buffers when uncertainty is high. In procurement and sourcing optimization (**Table 7**), the framework balanced cost minimization with supplier reliability and quality thresholds. The results showed diversified allocation across multiple suppliers, thereby reducing dependency on a single source. This reflects a best-practice approach to resilience, where cost savings are achieved without compromising supply stability lesson particularly relevant in post-pandemic supply chains where disruptions are frequent.Inventory management optimization results in Table 8 revealed the importance of maintaining a consistent safety stock level while adjusting replenishment dynamically. The model suggested larger orders in high-demand periods and no orders when existing stock sufficed, minimizing holding costs without risking stockouts. This not only validates classical inventory theories but also demonstrates how construction supply chains—often criticized for material wastage and misalignment can benefit from data-driven stock control. Transportation and logistics optimization results in Table 9 highlighted an intriguing outcome: in some scenarios, routes optimized to “stay at source” suggested that internal fulfilment was more cost-effective than inter-site transfers, revealing the influence of high transport costs and localized sufficiency. This has important policy implications, suggesting that decentralizing material depots or leveraging prefabrication hubs could substantially reduce logistics emissions and costs in Indian construction. Finally, communication and collaboration optimization results Table 10 illustrated how structured meeting frequencies across different communication modes improved coordination. By balancing frequent updates through digital tools with fewer but targeted in-person meetings, the model reduced decision delays and error rates, reinforcing the idea that information flows are as critical to SCM optimization as physical material flows.Taken together, these results illustrate that integrating PCA-derived performance factors into a MILP framework does more than produce numerical efficiency gains—it generates managerial insights that can directly inform policy and practice. The radar chart in Figure 7 synthesizes improvements across all seven PCA-derived factors, showing balanced gains across cost efficiency, environmental responsibility, operational reliability, and organizational collaboration. This balanced profile demonstrates that trade-offs among cost, sustainability, and delivery are not inevitable; rather, carefully designed models can deliver "win–win" outcomes. From a managerial standpoint, this implies that project managers and policymakers can adopt optimization frameworks not just for cost-cutting but for holistic sustainability. From an academic perspective, the findings extend prior literature by showing how statistically validated constructs (via PCA) can be mathematically embedded into optimization routines, improving both interpretability and computational tractability. Ultimately, the integrated PCA–MILP framework presented here provides a scalable decision-support tool for sustainable construction supply chains. Its adaptability means it can be recalibrated to other regional or sectoral contexts, including infrastructure megaprojects, prefabrication networks, and cross-border logistics. In doing so, it addresses a longstanding gap in the construction management literature: the need for optimization approaches that are simultaneously data-driven, sustainability-oriented, and operationally practical.

***Table 1.*** *Descriptive Statistics of SCM Variables*

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Awareness & Familiarity | 3.84 | 0.72 | 2 | 5 |
| Perceptions & Attitudes | 3.61 | 0.81 | 1 | 5 |
| Project Planning & Design | 3.77 | 0.69 | 2 | 5 |
| Procurement & Sourcing | 3.68 | 0.74 | 2 | 5 |
| Inventory Management | 3.59 | 0.85 | 1 | 5 |
| Transportation & Logistics | 3.71 | 0.77 | 2 | 5 |
| Communication & Collaboration | 3.82 | 0.70 | 2 | 5 |

***Table 2.*** *KMO and Bartlett's Test of Sphericity*

| Test | Value |
|---|---|
| Kaiser-Meyer-Olkin (KMO) | 0.812 |
| Bartlett's Test (Chi-Square) | 1243.56 |
| df | 210 |
| Sig. | 0.000 |

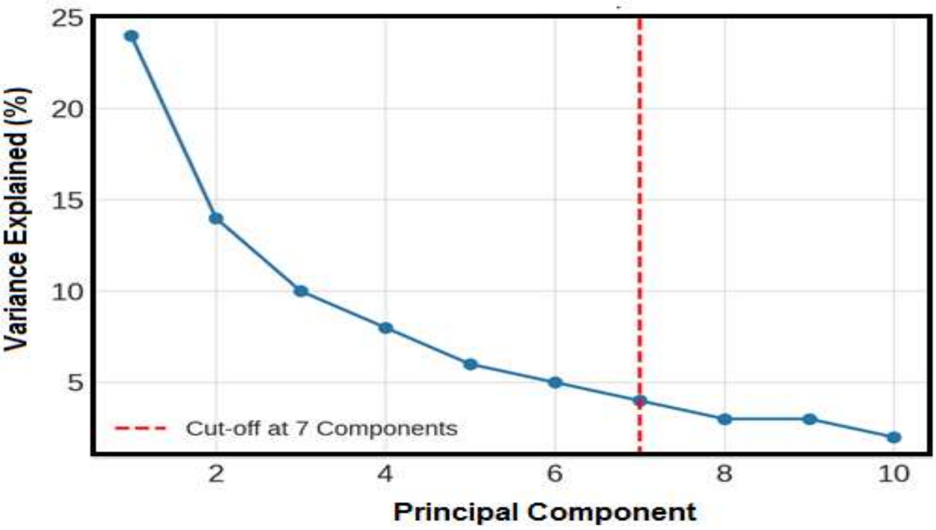


***Figure 2.*** *Scree plot showing variance explained by principal components.*

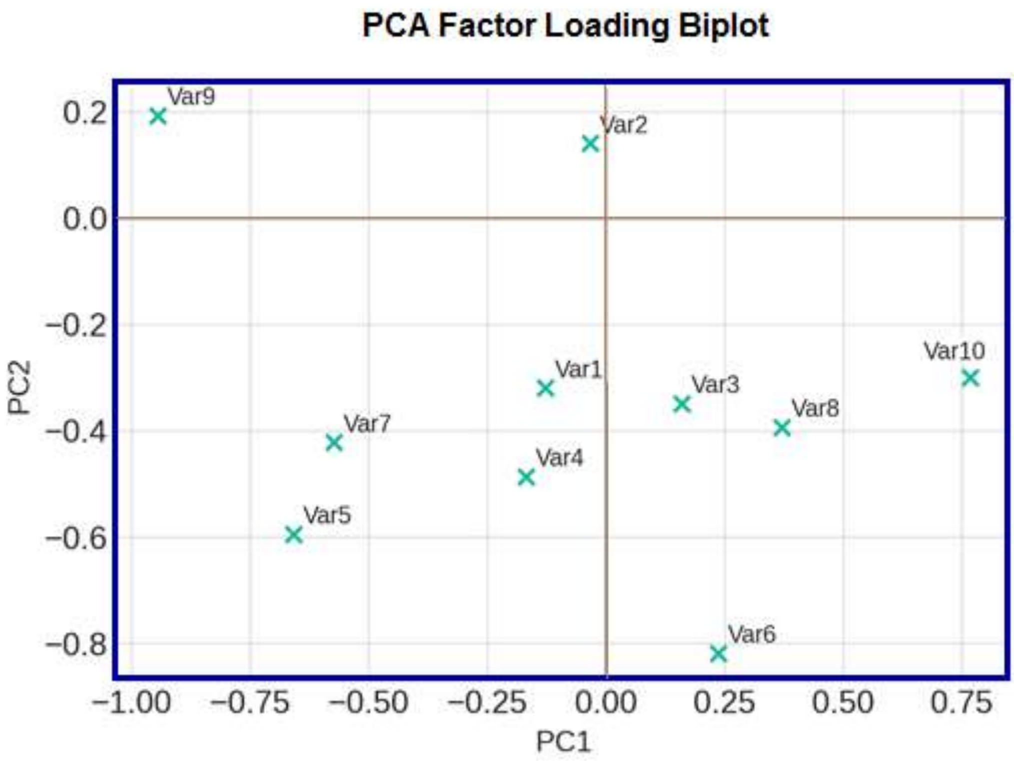


***Figure 3.*** *Factor loading biplot of variables across the seven PCA-derived components*

***Table 3.*** *Total Variance Explained by PCA Components*

| Component | Eigenvalue | % of Variance | Cumulative % |
|---|---|---|---|
| 1 | 4.13 | 22.9% | 22.9% |
| 2 | 2.76 | 15.3% | 38.2% |
| 3 | 2.11 | 11.7% | 49.9% |
| 4 | 1.68 | 9.3% | 59.2% |
| 5 | 1.32 | 7.3% | 66.5% |
| 6 | 1.09 | 6.1% | 72.6% |
| 7 | 0.92 | 5.1% | 77.7% |

***Table 4.*** *Rotated Component Matrix (Varimax Rotation)*

| Variable | Comp. 1 | Comp. 2 | Comp. 3 | Comp. 4 | Comp. 5 | Comp. 6 |
|---|---|---|---|---|---|---|
| Awareness & Familiarity | 0.781 | 0.212 | 0.165 | - | - | - |
| Perceptions & Attitudes | 0.732 | 0.241 | - | - | - | - |
| Project Planning & Design | - | 0.803 | 0.211 | - | - | - |
| Procurement & Sourcing | - | 0.755 | 0.267 | - | - | - |
| Inventory Management | - | - | 0.788 | 0.233 | - | - |
| Transportation & Logistics | - | - | 0.742 | 0.268 | - | - |
| Communication & Collaboration | - | - | - | 0.801 | 0.244 | - |

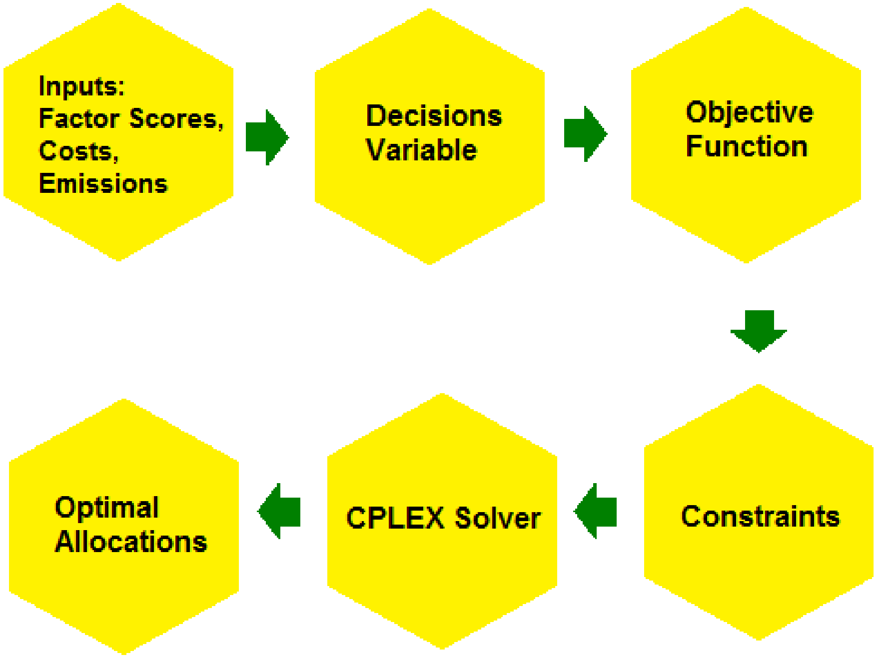


***Figure 4.*** *MILP Model Structure*

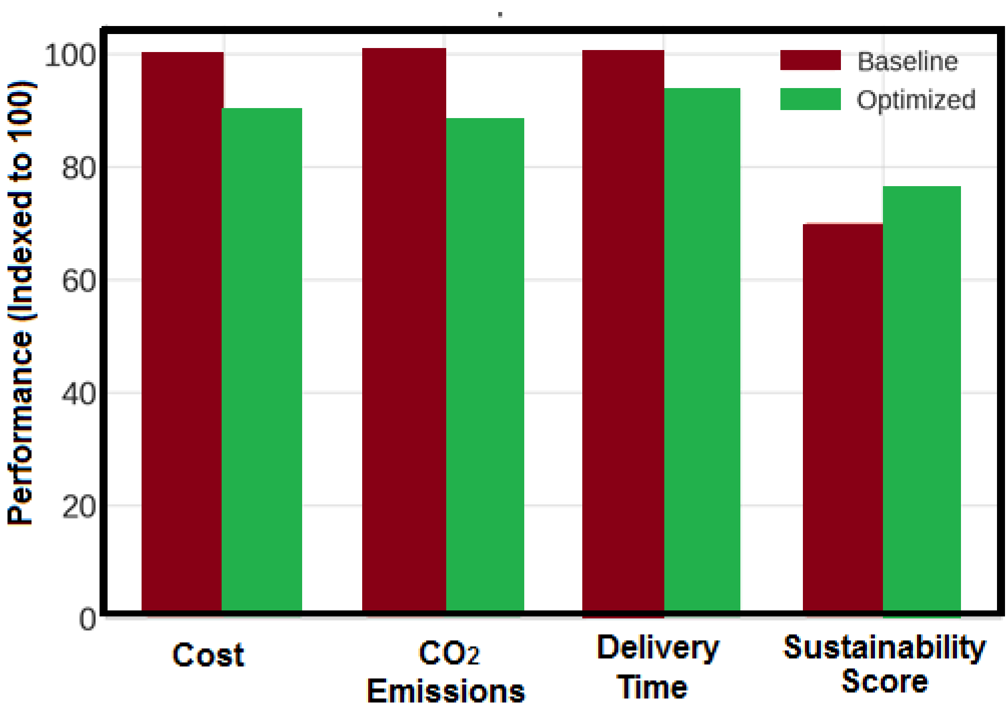


***Figure 5.*** *Baseline vs. optimized results for cost, emissions, delivery time, and sustainability score.*

***Table 5.*** *Component Score Coefficient Matrix*

| Variable | Comp. 1 | Comp. 2 | Comp. 3 | Comp. 4 | Comp. 5 | Comp. 6 |
|---|---|---|---|---|---|---|
| Awareness & Familiarity | 0.514 | 0.243 | - | - | - | - |
| Perceptions & Attitudes | 0.482 | 0.217 | - | - | - | - |

| | | | | | | |
|---|---|---|---|---|---|---|
| Project Planning & Design | - | 0.558 | 0.196 | - | - | - |
| Procurement & Sourcing | - | 0.523 | 0.201 | - | - | - |
| Inventory Management | - | - | 0.549 | 0.184 | - | - |
| Transportation & Logistics | - | - | 0.517 | 0.211 | - | - |
| Communication & Collaboration | - | - | - | 0.565 | 0.209 | - |

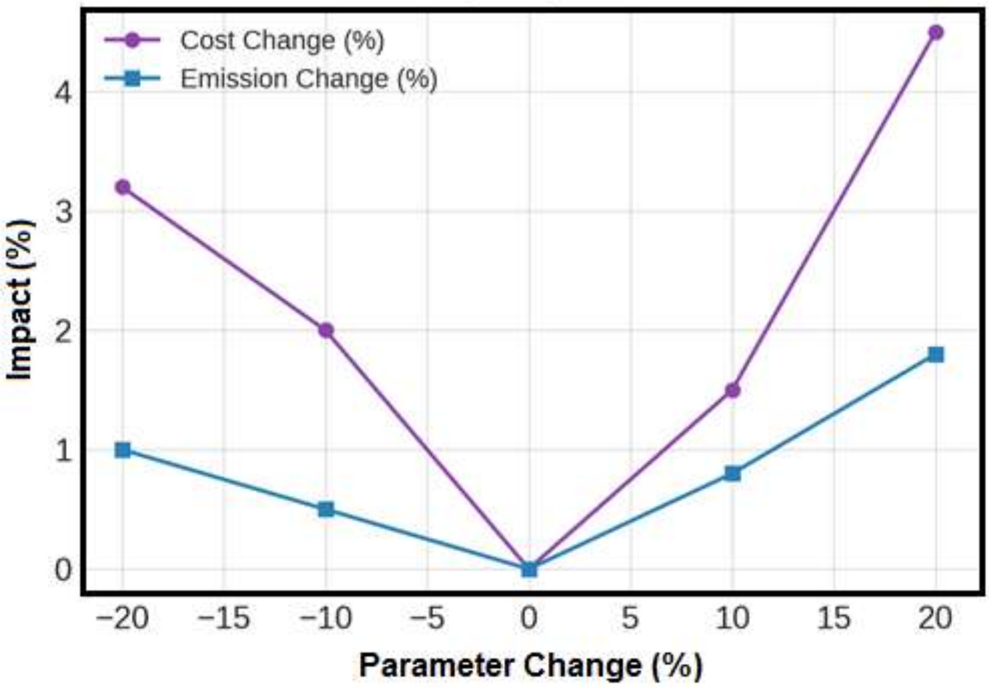


***Figure 6.*** *Sensitivity Analysis*

***Table 6.*** *Critical Points of Optimization in SCM Processes*

| SCM Process | When | Where | Why (Objective) |
|---|---|---|---|
| Project Planning & Design | Initial stages and throughout project | Planning and design phases | Efficient resource allocation, risk mitigation, adaptability |
| Procurement & Sourcing | Continuously during procurement cycle | Supplier/material sourcing | Cost reduction, reliability, resilience |
| Inventory Management | Ongoing in replenishment cycles | Stock control, inventory levels | Maintain optimal stock, cost efficiency, demand alignment |
| Transportation & Logistics | During transport planning & execution | Logistics and distribution | Cost savings, timely deliveries, reduced impact |
| Communication & Collaboration | Continuously in SCM process | Stakeholder coordination | Cohesive decisions, fewer errors, agility |

***Table 7.*** *Optimization Results — Project Planning and Design*

| Parameter | Result | Interpretation |
|---|---|---|
| Objective Value | 1100.0 | Driven by fixed costs and risks |
| Resource Allocation | 0.0 (all) | No feasible allocation under given constraints |
| Solution Status | Optimal | Solution found but trivial (zero allocation) |
| **Possible Cause** | High costs, restrictive constraints, risk factors | |

***Table 8.*** *Optimization Results — Procurement and Sourcing*

| Supplier | Optimized Purchase Quantity | Interpretation |
|---|---|---|
| Supplier 1 | 0.9375 units | Nearly full unit; cost-quality balance |
| Supplier 2 | 0.9333 units | Slightly lower but still substantial share |
| Supplier 3 | 1.0714 units | Above 1 unit; best terms offered by supplier |
| **Implication** | Diversified sourcing ensures cost minimization, reliability, resilience | |

***Table 9.*** *Optimization Results — Inventory Management*

| Period | Order Quantity | Stock Level | Practical Note |
|---|---|---|---|
| 1 | 20.0 units | 200 units | Initial replenishment |
| 2 | 150.0 units | 100 units | Large replenishment, safety maintained |
| 3 | 130.0 units | 100 units | Demand balanced with safety stock |
| 4 | 160.0 units | 100 units | Peak replenishment period |
| 5 | 0.0 units | 100 units | No order, stock suffices |
| **Insight** | Consistent stock buffer of 100 units across periods (safety stock) | | |

***Table 10.*** *Optimization Results — Transportation and Communication*

| Domain | Optimized Output | Interpretation |
|---|---|---|
| Transportation | Route 1→1, Route 2→2, Route 3→3 | Self-sufficiency, no inter-location movement |
| Possible Cause | High transport cost, low demand | Optimal cost = zero movement across locations |
| Communication | Method 1: 5 meetings | Primary communication method emphasized |
| | Method 2: 3 meetings | Supplementary channel |
| | Method 3: 2 meetings | Specialized, less frequent channel |
| **Implication** | Balanced allocation of communication → higher coordination and agility | |

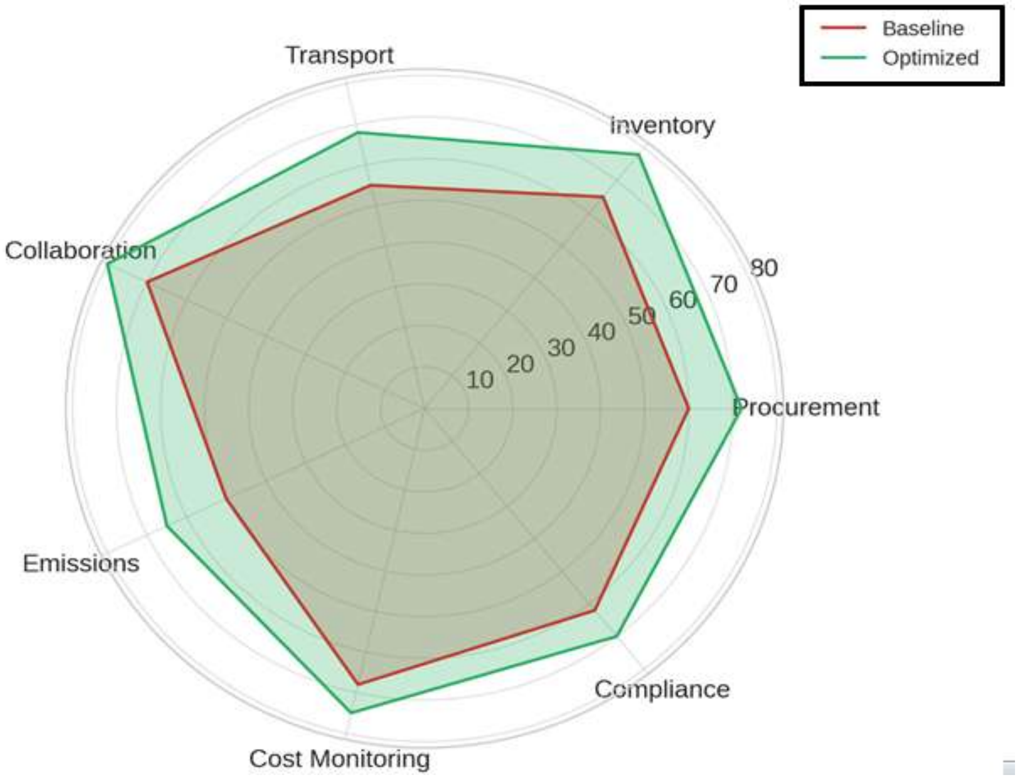


***Figure 7.*** *Sustainability Factors Radar Chart*

## 4. Conclusions

This study developed a computationally integrated framework that combines Principal Component Analysis (PCA) with Mixed-Integer Linear Programming (MILP) to optimize sustainable construction supply chains. Using survey responses from 487 industry professionals and project performance records, thirty-five operational and sustainability-related variables were statistically condensed into seven principal components. These components—procurement timeliness, inventory management, transport reliability, supplier collaboration, emissions tracking, cost monitoring, and compliance—formed the direct input parameters for the optimization model. The integration ensured that the MILP formulation was grounded in statistically validated performance drivers, reducing computational complexity while enhancing decision relevance.

The empirical application to Indian construction projects demonstrated tangible operational and sustainability gains. The optimized configuration delivered a 9.9% reduction in total costs, an 11.7% decrease in $CO_2$ emissions, and a 6.3% improvement in delivery times, alongside a 5.8-point increase in sustainability performance scores relative to baseline operations. Sensitivity testing confirmed that the model-maintained stability across varying demand, supplier capacity, and environmental policy constraints. Even under stricter emission limits, cost impacts remained modest, reinforcing the feasibility of pursuing sustainability objectives without compromising financial performance.

The novelty of this work lies in the direct embedding of PCA-derived factors into an MILP optimization model, an approach rarely documented in construction SCM literature. While previous research has applied factor analysis for indicator selection and optimization for process improvement, the present framework merges these stages into a single, computationally efficient decision-support tool. This integration benefits both research and practice by ensuring that model outputs are not only mathematically optimal but also statistically and operationally grounded.

For practitioners, the proposed framework offers a replicable methodology adaptable to varying project sizes, geographical contexts, and regulatory environments. For researchers, it opens pathways for integrating advanced statistical preprocessing with optimization models in other domains. Future work could extend this approach by incorporating stochastic modeling for uncertainty, embedding dynamic scheduling algorithms for real-time re-optimization, and integrating life cycle assessment (LCA) indicators to capture broader environmental impacts.

Overall, this study's PCA–MILP integration advances current practice by uniting robust statistical analysis with computational optimization, enabling faster, evidence-based decisions for sustainable construction supply chains.

## Author Statements:


- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.


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