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Bridging Theory and Prediction: A Hybrid SEM and Machine Learning Approach to Optimize Lean Construction for Megaproject Sustainability in China

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ABSTRACT

Construction megaprojects, large-scale, complex, and capital-intensive, are particularly prone to inefficiencies, cost overruns, delays, and environmental degradation due to fragmented workflows, stakeholder misalignment, and resource intensity. Lean Construction Practices (LCPs), with their focus on waste elimination, value stream optimization, and collaborative planning, offer a targeted response to these megaproject-specific challenges, directly supporting sustainability goals. However, empirical evidence on the systematic integration of LCPs into sustainable megaproject delivery, especially in emerging economies, remains sparse. This study addresses this gap by (1) quantifying the causal impact of LCPs on Overall Sustainable Success (OSS), defined as a tripartite construct encompassing environmental resilience (e.g., waste/energy reduction, pollution control), social inclusivity (e.g., worker safety, collaboration, equity), and economic efficiency (e.g., cost control, rework minimization, productivity gains), using PLS-SEM; and (2) identifying the most predictive LCPs for OSS using explainable Machine Learning (ML), with a focus on China, the world's largest megaproject market. Using survey data from 379 randomly sampled professionals engaged in megaprojects across Mainland China and Hong Kong, results confirm a strong LCP-OSS relationship ($\beta = 0.748$), with Gradient Boosting achieving 82% accuracy and 88% ROC-AUC. Crucially, SHAP analysis is innovatively applied at both indicator and construct levels, enabling actionable prioritization of LCPs, a methodological advance for sustainability research. Top practices include Safety and Quality Assurance (22.2%), Customer Focus and Waste Elimination (20.8%), and Standardization and Process Transparency (18.8%). While contextually grounded in China, findings align with SDGs 9, 11, and 12, suggesting transferability to similar emerging economies. The framework provides policymakers and practitioners with evidence-based levers to integrate sustainability into megaproject delivery, without compromising efficiency or equity.

1 | Introduction

Construction megaprojects are typically defined as large-scale, complex projects that require substantial investment (often exceeding $1 billion), involve multiple public and private stakeholders, take many years to develop and build, and have transformational impacts on millions of people, society, the economy, and the environment (Esposito and Terlizzi 2023; Pitsis et al. 2018). Yet, their substantial economic, social, and environmental footprints present persistent sustainability challenges, including excessive resource consumption, ecological degradation, community displacement, and governance inefficiencies (Thounaojam and Laishram 2022; Wang et al. 2020). While often heralded as catalysts for job creation, urban development, and technological advancement (Brockmann et al. 2016; del Cerro Santamaria 2019; Tripathi et al. 2023), megaprojects simultaneously exert considerable pressure on planetary boundaries. As one of the most resource- and emission-intensive sectors, the construction industry faces mounting expectations to align its practices with global sustainability imperatives (Bajjou and Chafi 2026; Rasheed O. Ajirotutu et al. 2024).

Despite growing awareness, the integration of sustainability into megaproject delivery remains hindered by systemic barriers: high upfront costs, fragmented stakeholder engagement, weak regulatory enforcement, limited adoption of green technologies, and the marginalization of sustainability goals within traditional project management paradigms (Coskun et al. 2023; Karji et al. 2020). Recent scholarship underscores the need for integrated, systems-oriented approaches that combine holistic frameworks, proactive stakeholder collaboration, technological innovation, and enabling policy environments to overcome these obstacles (Li et al. 2024; Tao et al. 2024).

In this context, LC has emerged as a promising paradigm to reconcile efficiency with sustainability. Rooted in waste elimination and value maximization, LC employs methodologies such as Just-in-Time (JIT) delivery and the Last Planner System (LPS) to streamline workflows, reduce variability, and enhance predictability (Carvajal-Arango et al. 2019; Suseelan and Vadivel 2024). Critically, these principles inherently support and actively advance core sustainability objectives. By minimizing material waste, optimizing energy use, improving labor conditions, and enhancing planning reliability, LC directly contributes to multiple United Nations Sustainable Development Goals (SDGs), including SDG 7 (affordable and clean energy), SDG 9 (industry, innovation, and infrastructure), SDG 11 (sustainable cities and communities), and SDG 12 (responsible consumption and production) (Hasan et al. 2024).

While lean practices are broadly applicable across project scales, megaprojects present unique challenges, including heightened complexity in stakeholder coordination among governments, multinational contractors, and local communities, and thus demand more sophisticated adaptations (Ibrahim et al. 2025a). Standardized lean tools, practical in conventional projects, often require customization, scalability, and deeper integration with digital technologies (e.g., BIM, IoT, AI-driven analytics) to address the elevated risks, interdependencies, and governance demands inherent in megaprojects (Ibrahim et al. 2026, 2025b; Pitsis et al. 2018). Accordingly, lean implementation in megaprojects necessitates context-sensitive frameworks that go beyond traditional applications, balancing standardization with adaptability to ensure resilience and sustainability at scale (Ibrahim et al. 2025c).

Empirical evidence highlights the multifaceted benefits of LC, encompassing environmental, social, and economic aspects. Nahmens and Ikuma (2012), for example, found that LC implementation yields substantial improvements across all three sustainability dimensions: a 64% reduction in material waste (environmental), the mitigation or elimination of critical safety hazards, such as excessive force, poor ergonomics, and struck-by incidents (social), and a 31% decrease in production hours (economic). Similarly, Bajjou and Chafi (2026) provide further quantitative validation, showing that core lean practices, particularly systematic waste reduction and disciplined planning and scheduling, exert a statistically significant positive effect on environmental performance. These benefits are further amplified when advanced LC techniques, such as Virtual Design and Construction (VDC) and the LPS, are strategically embedded across the project lifecycle and supply chain (Le and Nguyen 2024). Moreover, organizational enablers, including a culture of continuous improvement, leadership commitment, and process optimization, are critical to sustaining these outcomes over time (Dehdasht et al. 2023). Indeed, frameworks grounded in expert consensus suggest that integrating lean and sustainability principles early and holistically, from design through commissioning, unlocks synergistic effects, enabling more consistent, scalable, and resilient outcomes (Khanapure and Shastri 2024).

Nevertheless, a significant research gap persists. While LC's theoretical alignment with sustainability is well established, empirical validation, particularly in the context of megaprojects, remains limited (Chen et al. 2024; Hasan et al. 2024; Ibrahim et al. 2025c). This gap is consequential because megaprojects are not simply scaled-up versions of conventional projects; they exhibit *qualitatively distinct* characteristics that challenge the direct transferability of lean-sustainability insights. As emphasized by Hu et al. (2015) and Thounaojam and Laishram (2022), megaprojects are defined by their extreme scale, multi-actor fragmentation (often involving more than 30–50 contractors and subcontractors), long duration (typically exceeding 3–5 years), high political visibility, and deep socio-ecological embeddedness. These features amplify coordination failures, rework, and waste, precisely the issues LC seeks to mitigate, yet simultaneously undermine lean tools that rely on stable workflows, co-located teams, and trust-based collaboration (e.g., LPS, Kaizen circles). For instance, in conventional projects, JIT reduces on-site storage; in megaprojects, geographically dispersed workfaces and volatile supply chains may render strict pull systems infeasible without digital integration (e.g., BIM + IoT). Similarly, while 5S improves safety in factory-like settings, its efficacy in high-risk, dynamic megaproject environments (e.g., tunnelling, high-rise) depends on contextual adaptation (Enshassi et al. 2019). Critically, sustainability pressures in megaprojects, such as balancing rapid urbanization with SDG targets, introduce trade-offs (e.g., accelerated timelines versus community engagement) that are not fully addressed in extant lean models calibrated for smaller-scale, lower-stakes delivery. Hence, megaprojects warrant *dedicated empirical investigation* to identify which LCPs remain robust, how they must be adapted, and which emerge as uniquely critical in this context.

Additionally, much of the existing literature relies on qualitative case studies or conceptual models, with insufficient attention to quantitative, predictive, or causal analyses (Dixit et al. 2017; Khanapure and Shastri 2024; Khodeir and Othman 2018). Consequently, the complex interdependencies among Lean Construction Practices (LCPs) and their collective influence on

Overall Sustainable Success (OSS), encompassing environmental, social, and economic dimensions, are poorly understood, especially in large-scale, high-complexity settings.

Compounding this gap is a pronounced geographical bias: the majority of LC research originates from high-income countries such as the United States (e.g., Nahmens and Ikuma (2012); Song and Liang (2011)), leaving emerging economies underrepresented despite their escalating megaproject activity and urgent sustainability needs. Nowhere is this more evident than in China, which is currently executing the world's most extensive portfolio of infrastructure megaprojects amid rapidly evolving institutional and regulatory frameworks (Cheung and Shen 2017; Liu et al. 2018; Stoiian 2024). This context presents both a critical challenge and a unique opportunity to test and refine the integration of lean and sustainability in a dynamic, high-stakes environment.

This study is guided by the following central research question:

How can LCPs be effectively integrated into construction megaprojects to achieve OSS, and what contextual factors drive their adoption in emerging economies such as China?

In response, we propose a novel hybrid methodology that bridges explanatory theory with predictive analytics. First, we employ Partial Least Squares Structural Equation Modeling (PLS-SEM) to empirically test the causal relationships between specific LCPs and OSS dimensions within China's megaproject landscape. Second, we augment this structural analysis with machine learning (ML) algorithms, including random forest, support vector regression, and gradient boosting, to develop predictive models of OSS outcomes based on lean implementation patterns. This dual approach not only advances theoretical understanding of the LC-sustainability nexus but also delivers actionable, data-driven tools for practitioners and policymakers in emerging markets.

By integrating causal inference with predictive power, our framework offers a scalable pathway to align infrastructure development with global sustainability goals, particularly SDGs 9, 11, and 12, in contexts where the stakes for both economic growth and environmental stewardship are highest.

The remainder of this paper is structured to guide the reader from theoretical grounding to empirical validation and practical insight. Section 2 establishes the conceptual foundation by defining OSS across environmental, social, and economic dimensions and theorizing the pathways through which six LCP constructs influence OSS, culminating in Hypothesis 1. Section 3 details the hybrid methodology: first, PLS-SEM tests the causal relationships using data from 379 megaproject professionals in China; second, ML (with SHAP explainability) predicts OSS and prioritizes high-impact LCPs. Section 4 presents the empirical results, including both structural (e.g., $\beta = 0.748$) and predictive (e.g., 82% accuracy, SHAP rankings) aspects. Section 5 integrates and interprets these findings, highlighting the convergence and complementarity of SEM and ML insights, and discusses practical implications for policymakers and practitioners in emerging economies. Finally, Section 6 outlines the theoretical and methodological contributions. The conclusion section acknowledges limitations and proposes future research directions, particularly longitudinal and cross-regional validation.

2 | Research Background and Model Development

The concept of OSS in megaprojects encompasses long-term success across economic, social, and environmental dimensions, aligning with the SDGs. The economic dimension focuses on financial viability and positive economic impact (Coskun et al. 2023; Putri et al. 2023). Achieving this requires clear sustainability targets, robust regulatory frameworks, and the integration of environmental criteria across all planning, design, and execution phases. LCPs, with their emphasis on waste reduction, process optimisation, stakeholder collaboration, and continuous improvement, directly align with these requirements and thus hold strong potential as a strategic enabler for achieving OSS in megaproject delivery. Economically, LCPs improve performance by minimizing waste and optimizing resource flow. Lean Project Delivery (LPD), a core LC approach, supports value creation through collaborative planning. Carvajal-Arango et al. (2019) identify LPD as the most impactful LCPs approach for economic outcomes, reducing project variability and budget overruns by fostering stakeholder alignment. A core component of LPD is LPS, which Solaimani and Sedighi (2020) highlight for its effectiveness in resolving design and construction phase issues through real-time collaboration. By structuring workflows and enhancing communication, LPS reduces delays and rework, directly improving labor productivity and resource utilization (Aslam et al. 2021; Shaqour 2022). Complementing LPD, Kanban optimizes resource efficiency by limiting work-in-progress tasks and enabling JIT material delivery. Kanban minimizes idle time and storage costs, especially in modular construction, which is a highly trending approach due to its efficiency and sustainability advantages (Ali et al. 2023a; Banawi and Bilec 2014; Goh and Goh 2019). Similarly, Kaizen promotes continuous improvement, empowering workers to identify bottlenecks and reduce delays, thereby lowering labor and material costs (Babalola et al. 2019; Francis and Thomas 2019). The 5S methodology (Sort, Set in Order, Shine, Standardize, Sustain) further amplifies economic gains by streamlining workflows and reducing material waste, enabling faster project delivery and better budget adherence (Ahuja et al. 2017; Enshassi et al. 2019; Wu et al. 2020). Finally, Value Stream Mapping (VSM) serves as a visual diagnostic tool that helps teams identify and eliminate non-value-adding steps, thereby streamlining workflows and significantly reducing project cycle times (Carvajal-Arango et al. 2019; Saieg et al. 2018).

Social sustainability is supported by LC's emphasis on safety, participation, and teamwork. As evident in the literature, LPD and LPS promote stakeholder engagement and collaborative planning, thereby increasing accountability and reducing conflict. Gambatese et al. (2017) confirm LPD's role in reducing near misses and injury incidents by addressing the root causes of hazards, while Khodeir and Othman (2018) highlight LPD's broader social benefits, including reduced labor hours and improved working conditions. Central to LPD is the LPS, which engages workers and supervisors in collaborative planning, empowering them to control task scheduling and completion (Johnsen and Drevland 2016). This participatory approach enhances accountability, reduces conflicts, and strengthens teamwork (Weinheimer et al. 2017), thereby directly improving worker morale and commitment to project goals. LPS also mitigates safety risks by minimizing poor planning, thereby reducing accidents caused by rushed workflows (Awada et al. 2016). Complementing LPS, Kanban enhances social outcomes through visual management of workflows, which streamlines communication and reduces bottlenecks. Maris and Parrish (2016) note that Kanban's clarity in task coordination improves on-site safety, while Fuenzalida et al. (2016) link it to fewer accidents. By granting teams ownership over tasks, Kanban boosts worker satisfaction and fosters a culture of responsibility (Enshassi et al. 2019). Similarly, Kaizen promotes social equity by involving workers in identifying inefficiencies and safety risks, reinforcing their sense of value, and reducing turnover (Ahmed et al. 2021). Team-based problem-solving under Kaizen enhances communication and trust, which are critical for cohesive project execution (Khodeir and Othman 2018). The 5S methodology further enhances social sustainability by reducing site hazards, including congestion and slips. Anerao and Deshmukh (2016) and Francis and Thomas (2019) emphasize that organized workspaces minimize accidents, while regular inspections under 5S proactively address safety risks (Maris and Parrish 2016). This structured environment encourages shared responsibility, promoting teamwork and equity (Enshassi et al. 2019). JIT practices amplify these benefits by reducing clutter and material overstock, creating safer workspaces (Solaimani and Sedighi 2020). JIT's alignment of deliveries with project needs also reduces worker stress, enhancing job satisfaction (Saieg et al. 2018). Ultimately, the 5Whys analysis enhances safety culture by systematically investigating accidents and empowering workers to contribute to solutions (Osorio-Gómez et al. 2020).

On the environmental side, LC tools help reduce emissions, material waste, and pollution. LPS indirectly improves environmental outcomes by planning workflows more effectively and reducing rework, a key contributor to embodied carbon. For instance, LPS minimizes disruptions and rework, which is a significant source of embodied carbon, by resolving constraints (e.g., material availability, site conditions) upfront, as demonstrated by Ghosh et al. (2014)., who documented a 6% reduction in material waste and 7.5 MT CO2-equivalent emissions in a single process through LPS-driven coordination. Similarly, Salem et al. (2014) found that LPS reduced traffic instability in pavement projects, thereby cutting emissions from idling vehicles. Meanwhile, Ladhad and Parrish (2013) highlighted LPS's role in delivering a net-zero energy office by aligning teams around sustainability goals. These indirect environmental benefits of LPS complement tools like 5S, which directly mitigate pollution and hazards by organizing workspaces. Bae and Kim (2008) note that 5S supports LEED certification by reducing air/water pollution, while Salem et al. (2014) advocate its use in minimizing waste associated with pavement projects. JIT further reduces unfavourable environmental impacts by minimizing overstock and spoilage, though its success hinges on local material sourcing to avoid transportation-related emissions (Kim and Bae 2010). Prefabrication centralizes production in controlled environments, thereby reducing waste and emissions (Wu and Low 2010); however, strategic yard placement is crucial to avoid transportation trade-offs (Luo et al. 2005). Finally, VSM evolves into Sustainable-VSM (Sus-VSM) by incorporating environmental metrics (e.g., energy, emissions) to optimize processes, as seen in Rosenbaum et al.'s (2014) case study of a Chilean medical center, where material waste was reduced through the application of Sus-VSM. Figure 1 presents a comprehensive taxonomy of 35 LCPs, derived from a recent large-scale empirical study by Ibrahim et al. (2025d), and grouped into six theoretically grounded constructs. This taxonomy serves as the foundation for both measurement and analysis in this study.

It is increasingly recognized that sustainable megaproject delivery cannot rely on ad hoc or siloed interventions; instead, it demands a systemic, integrated assessment framework grounded in empirical evidence (Brunet 2025). Recent scholarship reflects this shift, with growing attention to sustainability-focused performance criteria that span the full project lifecycle, from planning through decommissioning, and emphasize reducing environmental externalities, ensuring long-term functional durability, and maintaining social legitimacy (Zhai et al. 2020). A landmark scientometric review by Wang et al. (2020), analyzing 134 studies, confirms that sustainability in megaprojects coalesces around three interdependent pillars: environmental (e.g., emissions mitigation, biodiversity protection), economic (e.g., life-cycle cost efficiency, value optimization), and social (e.g., labor welfare, inclusive governance, community resilience). Yet, the same review notes persistent fragmentation across disciplines, geographies, and project phases, highlighting the need for coherent, context-sensitive frameworks that can bridge theory and practice.

Critically, empirical work underscores the enabling role of institutional context, as noted by Zhai et al. (2020), drawing on data from 239 professionals in China. This study demonstrates that strong governmental governance, particularly in terms of policy coherence, regulatory enforcement, and stakeholder coordination, significantly enhances megaproject sustainability outcomes. This finding reinforces a broader scholarly consensus: megaproject sustainability is not merely a technical or managerial challenge, but a socio-political process shaped by power dynamics, institutional capacity, and normative commitments (Li et al. 2024; Thounaojam and Laishram 2022). As such, practical assessment must move beyond narrow operational metrics to embrace lifecycle-wide environmental stewardship, equitable social outcomes, and economically resilient delivery, all within the megaproject's unique scale, complexity, and embeddedness.

Following the triple-bottom-line (TBL) framework and aligned with SDGs 9 (Industry, Innovation & Infrastructure), 11 (Sustainable Cities & Communities), and 12 (Responsible Consumption & Production), we define Overall Sustainable Success (OSS) as an integrated construct capturing three interdependent dimensions:

1. *Environmental resilience*, reducing negative externalities (e.g., emissions, waste), and enhancing resource efficiency across project phases.

2. *Social inclusivity*, ensuring worker welfare, equitable stakeholder engagement, and community cohesion.

3. *Economic efficiency*, delivering value through cost control, quality assurance, and minimizing rework, *without* externalizing social or environmental costs.

FIGURE 1 | Taxonomy of LCPs grouped by construct and functional theme.

The selection of observed indicators for OSS (Table 1) followed by the theoretical grounding. Indicators were first identified through a systematic literature review, focusing on megaproject-specific sustainability frameworks (Brunet 2025; Coskun et al. 2023; Li et al. 2024). This evidence-based filtering yielded a concise yet comprehensive set of eight indicators, grouped under three latent dimensions, ensuring theoretical fidelity, contextual relevance, and replicability.

Based on the theoretical framework discussed above, and as illustrated in Figure 2, the following hypothesis is proposed:

H1. *The implementation of Lean Construction Practices (LCPs) has a significant positive impact on Overall Sustainable Success (OSS).*

3 | Methodology

The aim of this study is to examine the impact of LCPs on OSS in megaprojects within the context of emerging economies, with a particular focus on China. The proposed methodology is summarized in Figure 3. As we previously indicated, a hybrid framework

TABLE 1 | Latent variables and observed variables for assessing sustainable construction practices in megaprojects.

Category	CODE	Indicators	References
Environmental	WRE	Waste reduction and energy efficiency	(Brunet 2025; Coskun et al. 2023; Enshassi et al. 2016)
	PPG	Preventing air pollution and gas emissions	
Social	EEC	Enhance employees' commitment	(Brunet 2025; Coskun et al. 2023; Li et al. 2018)
	ISL	Improve overall safety for labours	
	ICC	Improve collaboration and communication	
	IIC	Improve interface and coordination	
Economic	RMI	Rework minimization, increased process efficiency, and cost savings	(Brunet 2025; Coskun et al. 2023; Enshassi et al. 2016)
	IQC	Increase the quality of construction processes	

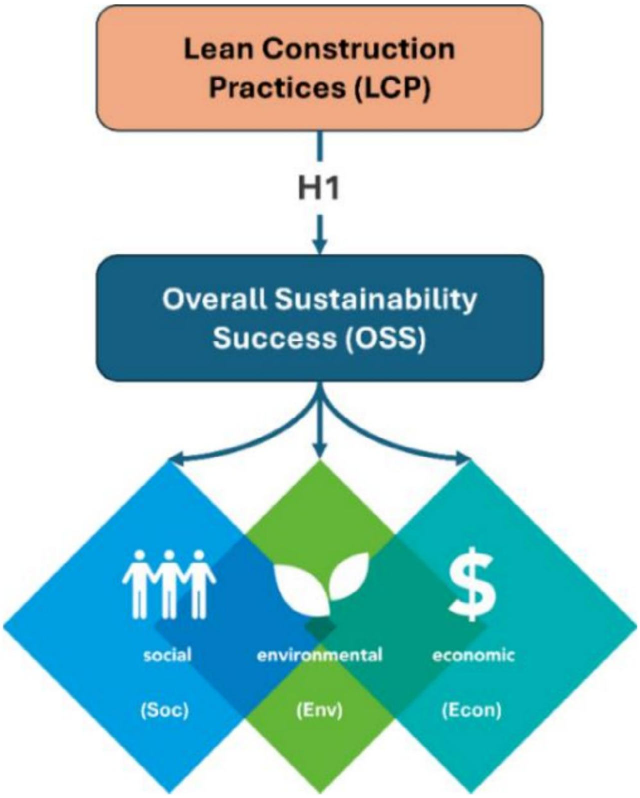

FIGURE 2 | Theoretical model.

was adopted, comprising two interconnected stages to examine how LCPs contribute to overall sustainable success in China.

Stage 1 focused on validating a theoretical model linking LCPs to OSS using PLS-SEM. The study commenced with a systematic literature review to identify core LCPs and key sustainability dimensions, namely environmental resilience, social inclusivity, and economic efficiency. The Scopus database was selected as the primary source due to its authoritative coverage of peer-reviewed research. A systematic PRISMA-based screening process, comprising identification, screening, eligibility, and snowballing, narrowed an initial pool of 267 records down to 82 relevant studies. These 82 articles formed the foundation for identifying LCPs and OSS indicators, with nine high-impact studies highlighted for their rigorous methodology and relevance to the constructs used in this research. A structured survey instrument was subsequently designed, refined through pilot testing, and deployed to 379 construction professionals engaged in megaprojects across China. To examine the causal relationships between LCPs and OSS, PLS-SEM was employed, enabling rigorous testing of hypothesized pathways and evaluation of model fit.

Stage 2 is more on predictive analytics, where ML models are used to predict OSS class based on LCP adoption. Note that multiple ML models were used, and we later select the best-performing model. To address class imbalance in the dataset, the Synthetic Minority Oversampling Technique (SMOTE) was applied during the preprocessing phase. Feature selection was then performed using only those variables identified as statistically significant in Stage 1 (PLS-SEM analysis), ensuring theoretical coherence between the explanatory and predictive modeling stages. Model performance was rigorously assessed using six evaluation metrics: accuracy, precision, recall, F1-score, ROC-AUC, and Matthew's Correlation Coefficient (MCC), providing a comprehensive view of predictive robustness across classification thresholds. While all metrics were computed, ROC AUC and MCC were prioritized for model comparison due to their robustness in multi-class settings and sensitivity to class-wise performance variation. Finally, SHAP values were applied to enhance model interpretability by quantifying the contribution of both individual LCP indicators (e.g., Kaizen, PPC Charts) and their broader construct-level groupings (e.g., People Involvement and Continuous Improvement, Safety and Quality Assurance) to OSS outcomes. While SHAP inherently explains predictions at the fine-grained feature level, we further aggregated SHAP values across indicators within each construct to assess the relative importance of the six main LCP categories, thereby offering insights at both granular and systemic levels of lean implementation.

3.1 | Survey Design and Data Collection

A questionnaire survey was selected as the primary data collection instrument, owing to its capacity to yield structured quantitative responses, essential for advanced statistical modeling, and its scalability in efficiently reaching a large, geographically dispersed sample (Young 2015). The instrument was organized

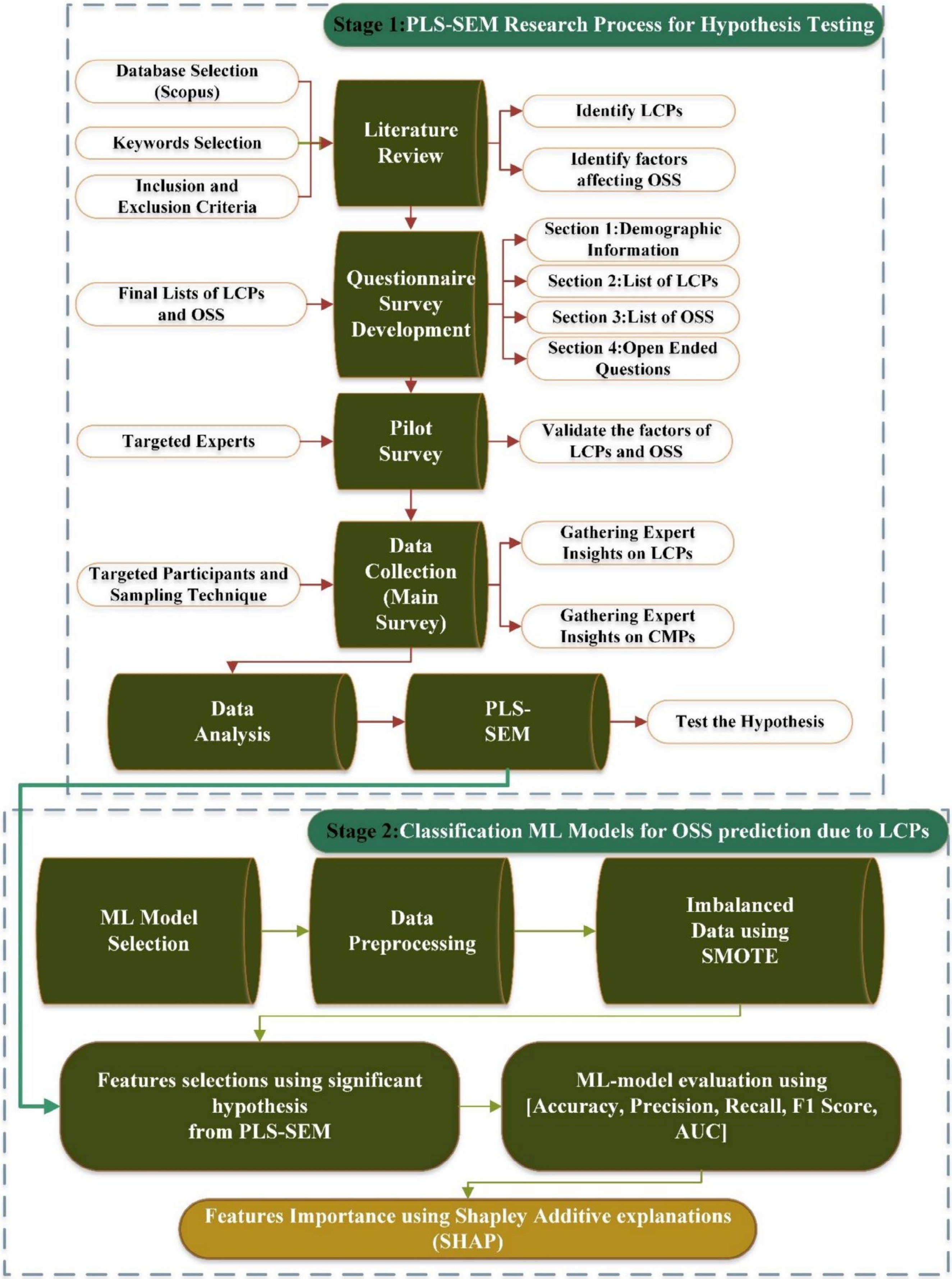

FIGURE 3 | Research methodology.

into four thematic sections: (1) demographic profiling to contextualize respondent backgrounds; (2) a curated list of LCPs for LCA, synthesized from an extensive literature review; (3) a set of OSS indicators, extracted through systematic analysis of scholarly sources; and (4) an open-ended item inviting participants to propose additional LCPs or OSS factors not captured in existing literature. Responses were captured using a 5-point Likert scale (1 = Very Low to 5 = Very High), measuring both the perceived adoption level of LCPs and the relative importance assigned to OSS dimensions.

The study targeted construction management professionals actively engaged in megaproject delivery, with a geographic focus on Mainland China and Hong Kong, regions selected for their high density of large-scale infrastructure initiatives and shared institutional and regulatory frameworks (Cheung and Shen 2017; Liu et al. 2018). In line with the approach taken by Wang et al. (2021), projects exceeding 0.5 billion CNY in investment were classified as megaprojects, ensuring alignment with established economic thresholds for complexity and scale. To enhance generalizability and reduce sampling bias, participants were selected using a random sampling technique, a method widely validated in social science research for its capacity to yield representative and statistically robust samples (Olanrewaju et al. 2022).

Data were collected between March and September 2024. Guided by Badewi (2016), the target sample size was determined based on the analytical requirements of the study. As SEM was employed, a minimum of 100 valid responses was necessary to ensure statistical reliability, a threshold supported by Ali et al. (2023b). Out of 471 total submissions, 379 questionnaires met completeness and consistency criteria, resulting in an effective response rate of 80.46%. The survey instrument focused on measuring respondents' perceptions of LCPs and their influence on OSS.

3.2 | Development of the PLS-SEM Model

Structural Equation Modeling (SEM) is a robust multivariate analytical technique used to empirically test theoretical frameworks by evaluating complex relationships among latent constructs and their measured indicators. A defining advantage of SEM is its capacity to simultaneously estimate direct and indirect effects within hypothesized causal networks, offering greater analytical depth than traditional regression-based approaches (Fan et al. 2016). Model validation follows a two-step protocol: first, the measurement model is assessed via Confirmatory Factor Analysis (CFA) to ensure that the observed variables reliably represent their underlying constructs; second, the structural model is evaluated through path analysis to test the significance and direction of the proposed inter-construct relationships (Xiong et al. 2015). SEM is widely applied in disciplines like management and construction management (Elrifaee et al. 2025; Ibrahim and Zayed 2025; Oyewobi et al. 2016). This study employs PLS-SEM over covariance-based SEM (CB-SEM) due to its superior predictive capabilities, stronger statistical framework for evaluating multiple constructs, and ability to account for experimental variance (Hair, Risher, et al. 2019). The objective is to assess the predictive performance of a theoretical model and the relationships between LCPs and OSS in megaprojects. Figure 4 clarifies the components and the validation tests used in the PLS-SEM model.

As shown in Figure 4, the PLS-SEM process begins with a thorough assessment of the measurement model to establish both convergent and discriminant validity, which are foundational criteria for construct robustness.

Convergent validity was evaluated using four complementary metrics: outer loadings, composite reliability (CR), Cronbach's Alpha (α), and Average Variance Extracted (AVE). Outer loadings, indicating the strength of association between each indicator and its assigned latent variable, were required to meet or exceed 0.70 to ensure meaningful contribution (Hair Jr et al. 2021). Composite reliability, preferred over Cronbach's Alpha for its superior handling of tau-equivalence, was expected to surpass 0.70 in confirmatory contexts; however, a threshold of 0.60 was deemed acceptable for exploratory research (Hock et al. 2010). While Cronbach's Alpha is recognized for its limitations, particularly its sensitivity to scale length and item homogeneity, values above 0.60 were retained as supportive evidence when aligned with CR benchmarks. Finally, AVE, representing the proportion of variance in indicators explained by their underlying construct, was required to exceed 0.50 to affirm strong convergent validity (Memon and Rahman 2014).

Discriminant validity, which confirms that constructs are empirically distinct, was verified using two established approaches: the Fornell–Larcker criterion and cross-loadings analysis. Per the Fornell–Larcker method, the square root of each construct's AVE must be greater than its correlation with any other construct, ensuring that constructs share more variance with their own indicators than with those of others (Memon et al. 2017). The cross-loadings test further reinforces this by requiring each indicator to load more strongly on its designated construct than on any competing construct, a critical check for conceptual uniqueness (Yu et al. 2021).

Once the measurement model has been validated, attention shifts to evaluating the structural model through bootstrap resampling. This non-parametric technique generates empirical estimates of standard errors and confidence intervals by repeatedly sampling from the original dataset (Hair et al. 2014). Bootstrap analysis enables researchers to determine the statistical significance of path coefficients, providing robustness to the findings. Two key outputs are examined: the standardized path coefficient (β-value), which indicates the magnitude and direction of the relationship between constructs, and the corresponding p-value, which reflects the statistical significance of that relationship (Leguina 2015). A β-value ≥ 0.09 is considered meaningful, with higher values reflecting stronger effects (Hussain et al. 2018). p-values ≤ 0.05 confirm that observed relationships are unlikely due to chance, validating their statistical relevance (Hair et al. 2013; Leguina 2015).

To evaluate the structural model's explanatory power, predictive accuracy, and practical relevance, three complementary indices were employed: the Coefficient of Determination (R^2), Predictive Relevance (Q^2), and Effect Size (f^2). R^2 quantifies the proportion of variance in endogenous constructs explained by their predictors, with values interpreted as weak (0.02–0.13), moderate (0.13–0.26), or substantial (> 0.26) (Olanrewaju et al. 2021). Q^2, derived through blindfolding procedures, assesses the model's out-of-sample predictive capacity; a value exceeding zero

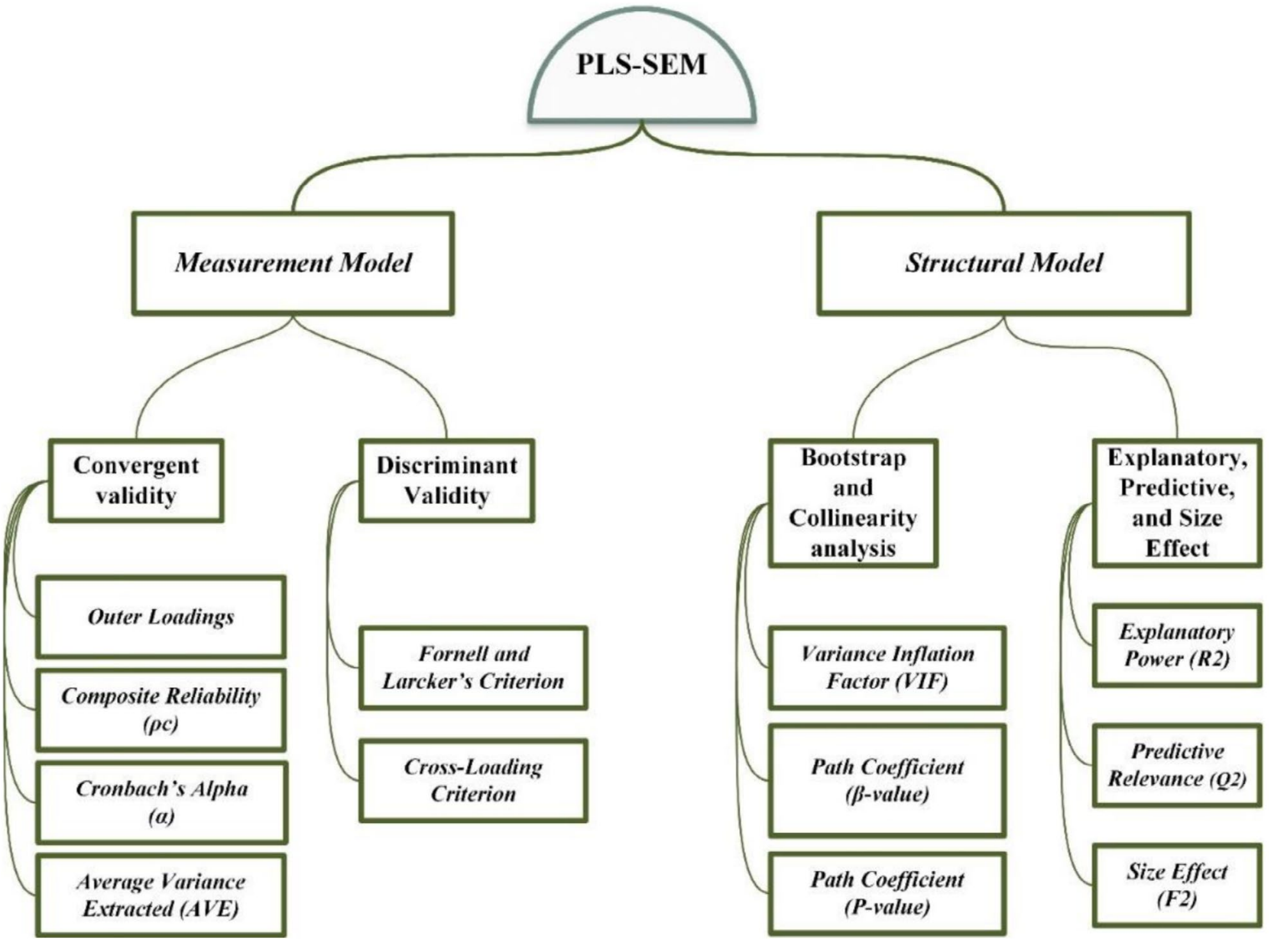

FIGURE 4 | PLS-SEM analytical framework.

confirms meaningful predictive relevance beyond the observed dataset (Hair et al. 2014; Hair, Black, et al. 2019). Finally, f^2 measures the local impact of each exogenous construct on its dependent variable, with effect magnitudes classified as small (0.02–0.15), medium (0.15–0.35), or large (>0.35), offering insight into the relative importance of individual drivers (Hair, Black, et al. 2019).

3.3 | Machine Learning Models and Explainability

As previously outlined, this study employs a hybrid analytical strategy: it first tests theoretical relationships using PLS-SEM, then leverages the statistically significant variables identified in that phase as input features for ML-based predictive modeling. A hybrid PLS-SEM and ML approach was adopted to overcome the limitations of either method alone: PLS-SEM provides causal plausibility and construct validation, while ML (especially tree-based ensembles) offers nonlinear predictive power and handles interaction effects that SEM may miss (Alshurideh et al. 2023; Richter and Tudoran 2024). Crucially, using SEM-significant variables as ML inputs ensures *theoretical grounding*, avoiding the "black box" criticism of purely data-driven models (Wang, Liang, et al. 2024; Wang, Wang, et al. 2024). To operationalize the prediction task, the dataset was pre-processed and framed as a multiclass classification problem, wherein levels of OSS are predicted based on patterns of LCP adoption.

A diverse set of ML algorithms was tested to ensure comprehensive model evaluation. The classifiers included Random Forest, XGBoost, AdaBoost, Gradient Boosting, Support Vector Classifier (SVC), Decision Tree, Logistic Regression, Extra Trees, Linear Discriminant Analysis (LDA), k-Nearest Neighbors (kNN), Artificial Neural Networks (ANN)/Multilayer Perceptron (MLP), and Naive Bayes. The selected ML models span diverse algorithmic families, enabling robust performance benchmarking and enhancing the generalizability of the findings. Tree-based ensemble models (Random Forest, Gradient Boosting, AdaBoost, XGBoost, Extra Trees) are widely used in construction and sustainability studies due to their ability to model complex nonlinear interactions, handle multicollinearity, and provide feature importance rankings. Logistic regression and LDA offer interpretable baselines for linear classification. ANN can capture deeper interactions but is more sensitive to tuning. SVC is effective in high-dimensional spaces. K-NN and Naive Bayes were included for completeness and to examine their behaviour on this type of structured, tabular dataset. This diverse set ensures that the final model choice is not biased by algorithm class, enabling a reliable comparison across different modeling paradigms. These algorithms were selected based on their prior use in construction and sustainability research, computational efficiency, and proven ability to handle medium-sized structured datasets. Table 2 summarizes the use of these classifiers in related studies. Our dataset has a size of 379, which aligns well with typical sizes used in similar construction-focused research. As Lakens (2022) emphasizes, predictive modeling does not adhere to rigid sample size requirements; our dataset falls well within empirically acceptable ranges for the ML algorithms employed. To ensure rigorous evaluation and fair comparison across models, performance was assessed using a comprehensive suite of standard metrics: accuracy, precision, recall, F1-score, ROC-AUC, confusion matrix analysis, and Matthew's Correlation Coefficient (MCC), collectively offering a balanced view of predictive power, class-wise performance, and overall reliability.

To improve the interpretability of the ML models, SHAP was applied. SHAP, over alternatives like LIME or permutation importance, was selected for its game-theoretic consistency, global–local interpretability, and growing adoption in construction analytics for fair, additive attribution (Oluleye et al. 2024; Wang, Liang, et al. 2024). SHAP values quantify the contribution of each input feature (i.e., LCP practice) to the model's predictions. This method is based on cooperative game theory and provides both global (overall feature importance) and local (instance-level) explanations. By assigning a consistent and theoretically grounded importance value to each LCP, SHAP helps clarify which practices have the most significant influence on sustainability outcomes. This supports actionable insights by linking model predictions directly back to management decisions on LCP adoption (Wang, Liang, et al. 2024).

4 | Data Analysis and Results

4.1 | PLS-SEM Results

4.1.1 | Measurement Model

Before testing structural relationships, the measurement model was validated for reliability and validity using convergent validity, discriminant validity, and internal consistency checks.

4.1.1.1 | Convergent Validity. Most key constructs, including CWE, FPS, PAS, PCI, SPT, SQA, and OSS, exhibited strong outer loadings above 0.70, with some reaching a value of up to 0.890. Two weak indicators (CWE4 and PCI7) were removed to refine the model, resulting in improved construct-indicator alignment as shown in Figures 5 and 6. Reliability and convergent validity were confirmed across all constructs, with Composite Reliability values exceeding 0.80 (and ≥ 0.90 for PCI, SPT, and SQA), Cronbach's Alpha consistently above 0.60, and AVE scores meeting the 0.50 threshold as shown in Table 3. Collectively, these results verify the robustness of the measurement model, establishing a solid foundation for subsequent structural analysis and reinforcing the study's methodological rigor.

4.1.1.2 | Discriminant Validity. Discriminant validity was assessed using cross-loadings and the Fornell–Larcker criterion. Cross-loading analysis confirmed that all indicators loaded more strongly on their respective constructs than on any alternative construct. For example, CWE1–CWE3 (Customer Focus and Waste Elimination) showed primary loadings between 0.716 and 0.802 on the CWE construct, with noticeably weaker associations with Economic, Environmental, and Social dimensions. Similar patterns were observed across FPS, PCI, PAS, SQA, Soc, and SPT, such as FPS4 loading highest on FPS ($\lambda = 0.832$) and SPT6 loading strongest on SPT ($\lambda = 0.703$). No indicator demonstrated a higher loading on a competing construct, confirming the distinctiveness of all latent variables. The Fornell–Larcker results in Table 4 further reinforce this finding: in every case, the square root of each construct's AVE (reported on the diagonal) exceeded its correlations with other constructs. Collectively, these outcomes demonstrate strong discriminant validity, confirming that each construct uniquely captures its intended theoretical domain.

TABLE 2 | ML classifier in prior research.

	Oluleye et al. (2024)	Elnabwy et al. (2025)	Wang, Wang, et al. (2024)	Ayhan et al. (2021)	Sanni-Anibire et al. (2022)
Random forest	✓				
Xgboost	✓				
AdaBoost				✓	
Gradient boosting	✓				
Decision tree	✓				
Support vector classifier	✓			✓	✓
Logistic regression	✓	✓			
Extra tree classifier		✓			
Linear discriminant analysis (LDA)		✓			
ANN/MLP-classifier			✓	✓	✓
k-nearest neighbors (kNN)			✓	✓	✓
Naive bayes classifier			✓	✓	

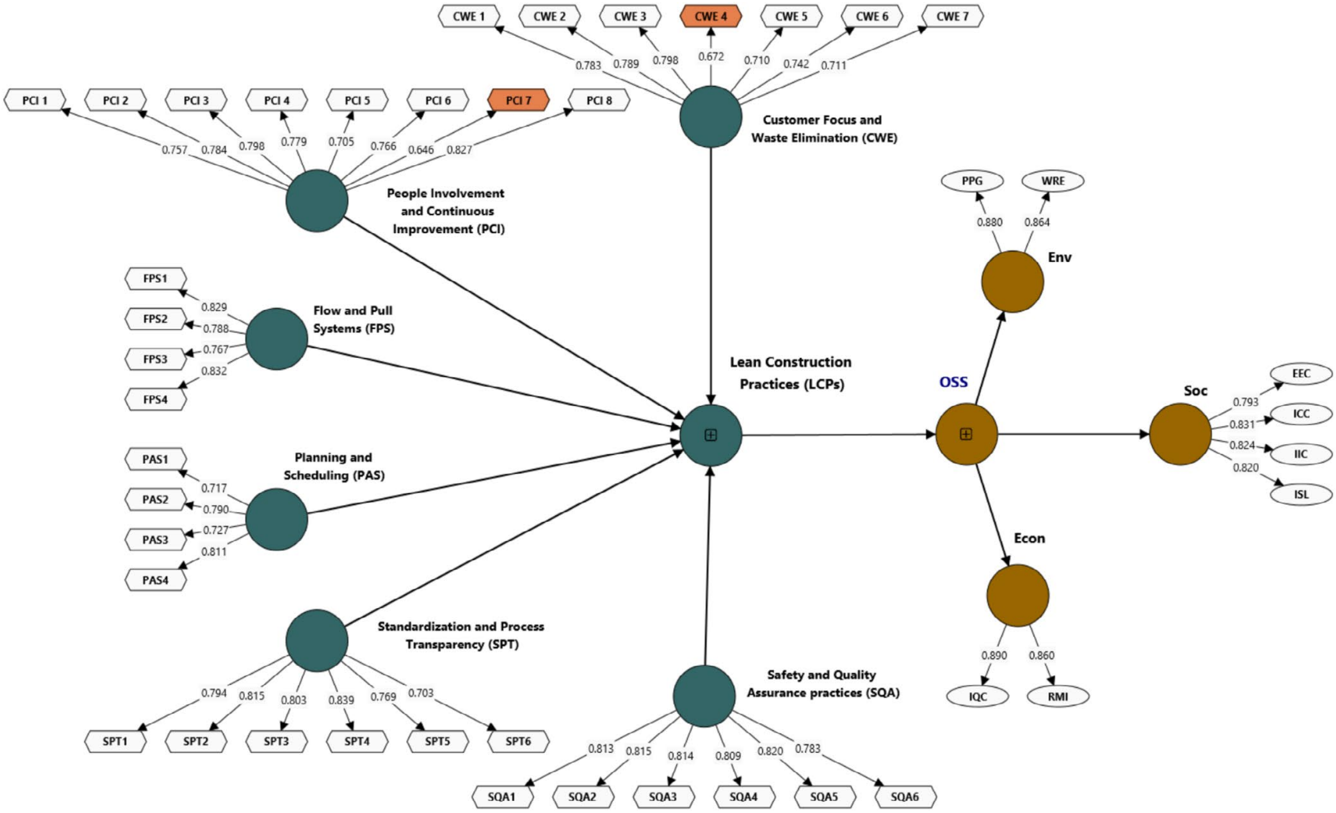

FIGURE 5 | The PLS-SEM initial model.

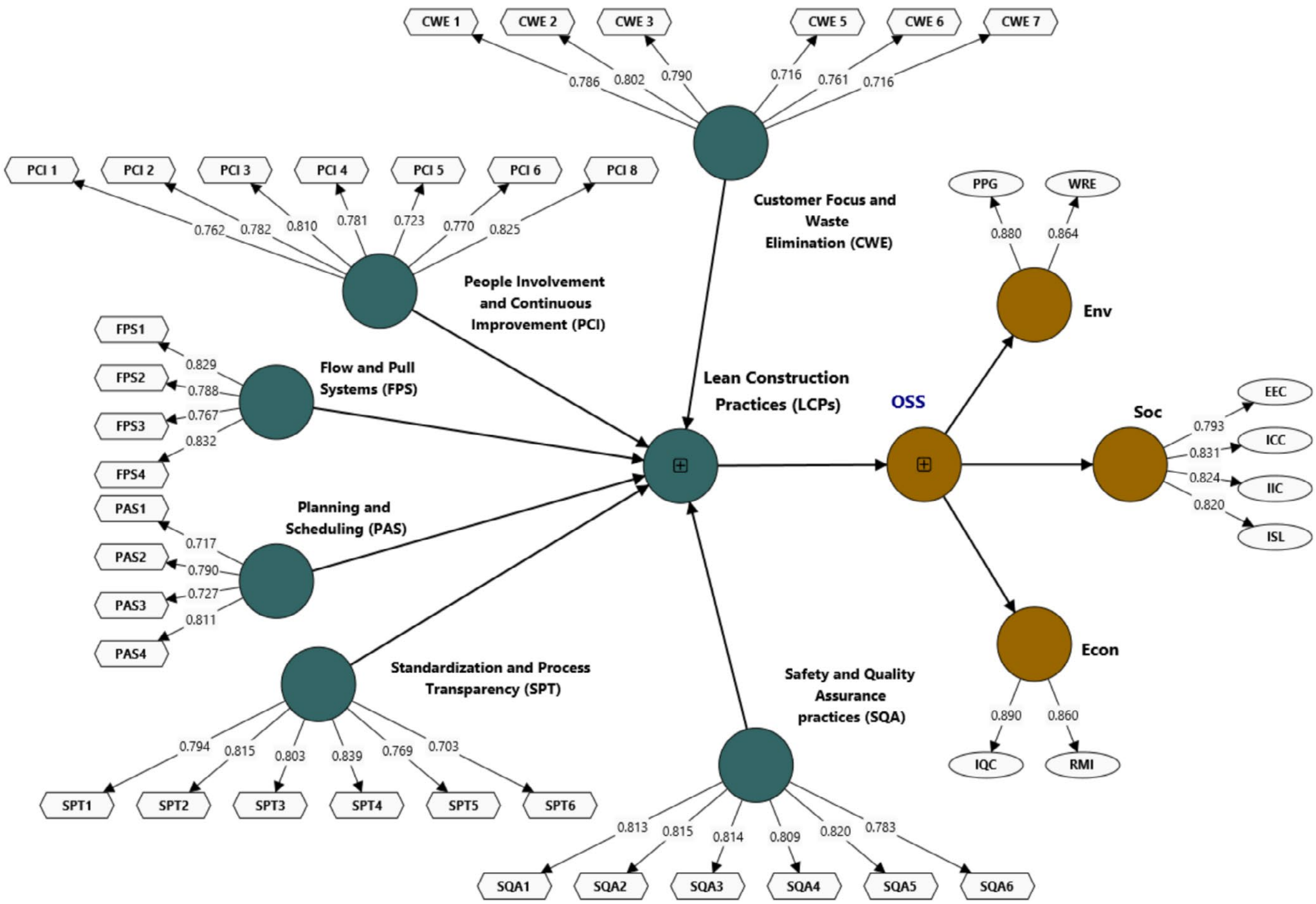

FIGURE 6 | The PLS-SEM final (modified) model.

4.1.2 | Structural Model

The validity and explanatory power of the structural model were evaluated in two stages. First, Variance Inflation Factors (VIF) were computed to assess multicollinearity among predictors; all values fell below the conservative threshold of 5, indicating no problematic collinearity (Hair et al. 2017). Second, model performance was assessed using four core metrics: path coefficients (β), coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Notably, the model yielded an R^2 of 0.559, meaning that 55.9% of the variance in OSS, the dependent construct, is accounted for by the LCPs, as visually summarized in Figure 7. This underscores the model's explanatory power in capturing relationships between sustainability practices and LCPs. Additionally, the relationship between LCPs and Overall Sustainability Success (OSS) was highly significant ($p = 0.748$, $p < 0.000$), emphasizing the critical role of LCPs as foundational enablers for embedding sustainability into megaprojects. The model's predictive relevance is further substantiated by a Q^2 value of 0.566, well above zero, indicating its capacity to generate accurate out-of-sample predictions. Additionally, the effect size (f^2) of 0.748 indicates a significant practical impact, confirming that the predictor constructs (LCPs) have a considerable influence on the endogenous variable (OSS). Together, these results, combined with the high R^2, confirm that the structural model is not only statistically sound but also practically meaningful, providing a robust and reliable framework for understanding how LCPs influence sustainability outcomes in megaprojects.

TABLE 3 | Summary of reliability and convergent validity assessments.

Category	Cronbach's alpha	Composite reliability	AVE
Environmental sustainability (Env)	0.69	0.86	0.76
Social sustainability (Soc)	0.83	0.89	0.67
Economic sustainability (Econ)	0.70	0.87	0.77
Customer focus and waste elimination (CWE)	0.86	0.89	0.58
Standardization and process transparency (SPT)	0.88	0.91	0.62
People involvement and continuous improvement (PCI)	0.89	0.92	0.61
Planning and scheduling (PAS)	0.76	0.85	0.58
Flow and pull systems (FPS)	0.82	0.88	0.65
Safety and quality assurance practices (SQA)	0.89	0.92	0.65

4.2 | Predicting OSS Using ML

The framework follows a sequential and role-separated design. PLS-SEM is first used for theory testing and measurement validation. At this stage, observed indicators are evaluated for reliability and convergent validity within their latent constructs. Indicators with insufficient outer loadings are removed as part of standard measurement model refinement. The remaining indicators are therefore measurement-valid and theoretically grounded. All retained observed indicators are then used directly as input features for the ML models. SEM residuals and latent variable scores are not used in the ML stage, and no additional *p*-value–based filtering is applied after SEM. Accordingly, PLS-SEM is used for construct validation only and does not function as a feature selection mechanism for ML.

The dataset is a two-dimensional array with 379 rows and 34 columns: 33 input features and one target variable. The 33 input features correspond to the individual LCP items retained after PLS-SEM validation (i.e., all original items except CWE4 and

TABLE 4 | Correlation of constructs (Fornell-Larcker).

	CWE	Econ	Env	FPS	PCI	PAS	SQA	Soc	SPT
CWE	**0.761**								
Econ	0.646	**0.875**							
Env	0.595	0.697	**0.872**						
FPS	0.726	0.601	0.577	**0.806**					
PCI	0.753	0.653	0.589	0.777	**0.781**				
PAS	0.691	0.632	0.547	0.764	0.706	**0.761**			
SQA	0.745	0.676	0.630	0.754	0.683	0.693	**0.806**		
Soc	0.662	0.791	0.808	0.644	0.673	0.619	0.688	**0.819**	
SPT	0.750	0.659	0.629	0.640	0.676	0.710	0.675	0.699	**0.787**

Note: The diagonal bold numbers are important to report the results.

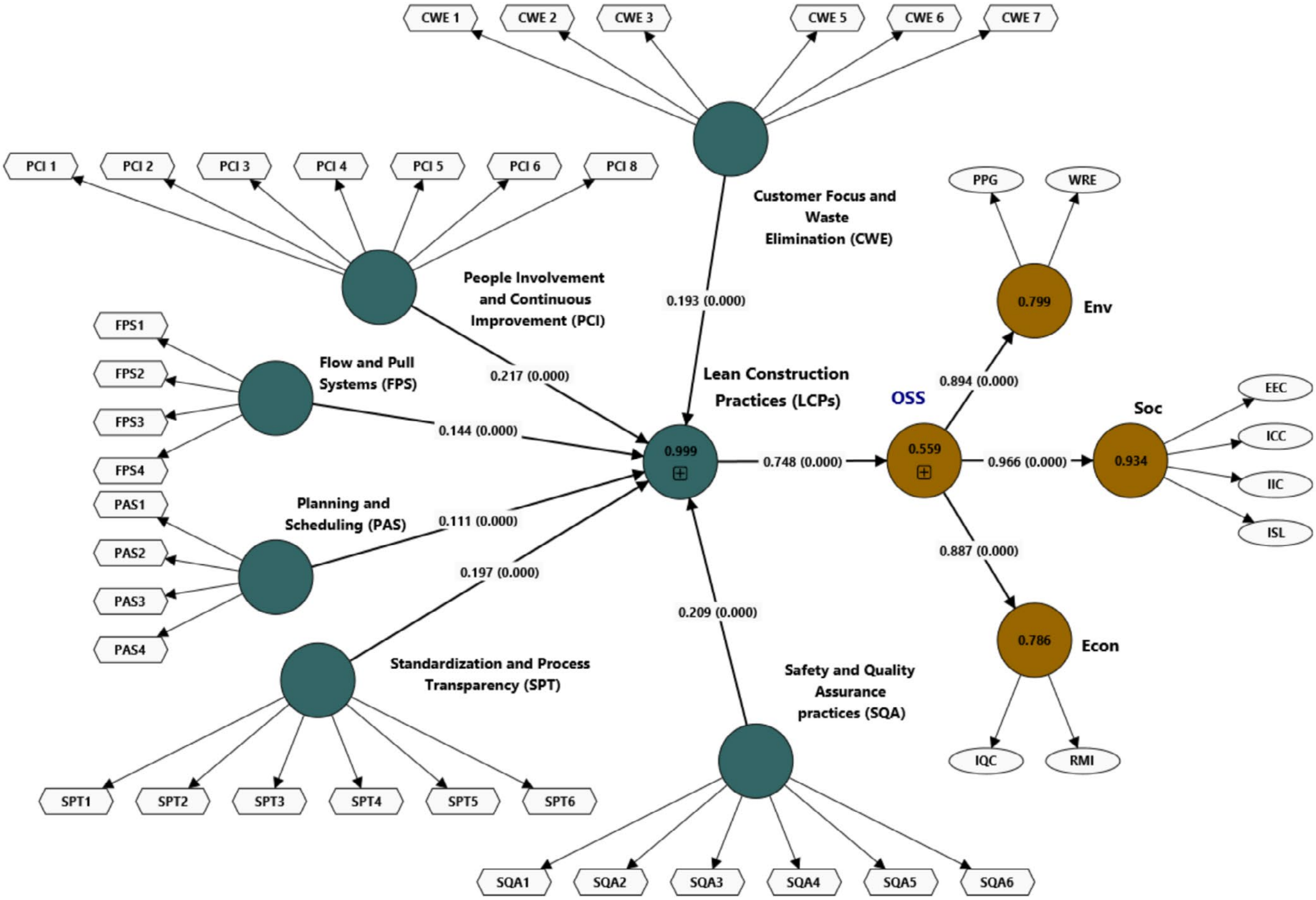

FIGURE 7 | Structural model: Path coefficient.

PCI7, which were removed due to outer loadings < 0.70). These Likert-scale responses were used directly as raw input features, rather than latent scores or residuals, to preserve behavioral granularity.

The target variable, OSS, was derived by computing the mean of the eight validated OSS indicators (WRE, PPG, EEC, ISL, ICC, IIC, RMI, IQC) for each respondent. This composite score, representing holistic sustainability perception, was then discretized into three ordinal classes (low/medium/high) using natural breaks (DiStefano et al. 2021; Fernández et al. 2018), enabling robust multiclass classification. The key steps of the data preprocessing, feature selection, and model training process are summarized in Figure 8.

A key issue identified during exploration was class imbalance. Some OSS levels have fewer samples than others, which leads to biased model learning and poor generalization. He and Garcia (2009), there is no universally optimal solution to this problem. To address this, we define three OSS classes: low, medium, and high (DiStefano et al. 2021; Fernández et al. 2018). To further solve the imbalance issue, we use SMOTE. In contrast to conventional oversampling techniques that simply duplicate instances from the minority class, the Synthetic Minority Oversampling Technique (SMOTE) creates artificial samples by interpolating between existing minority class observations within the feature space (Rakhshan et al. 2023). This method provides notable benefits compared to traditional approaches such as random oversampling, undersampling, and other synthetic data generation strategies. In this study, SMOTE was applied to the training dataset per the procedure outlined by Wongvorachan et al. (2023), leading to a more balanced class distribution. The dataset, which initially consisted of 245 high, 120 medium, and 14 low OSS impact examples, was transformed into a balanced distribution of 200 instances for each class. The dataset was then randomly split into training and test sets using an 80/20 ratio.

Before training the ML models, all features significantly associated with OSS identified through PLS-SEM analysis were included in the model development process. Feature selection was then performed using the SelectKBest algorithm with the ANOVA F-value scoring function as the selection criterion. This choice was particularly appropriate for our multiclass classification problem, where the target variable (OSS) comprised three ordinal classes (low/medium/high) while the input features were derived from Likert-scale responses (treated as continuous variables). The ANOVA F-value effectively measures the linear dependency between each feature and the target classes by comparing the variance between classes to the variance within classes. The SelectKBest method assessed various feature proportions to refine the feature set further, specifically evaluating performance at proportions of 100%, 90%, 80%, and 70% of the original feature set. However, the results indicated that reducing the number of features did not improve model performance across any of the tested ML algorithms. This outcome aligns with our theoretical framework regarding Lean Construction

Practices, which posits that these practices function synergistically rather than in isolation.

As shown in Table 5, the predictive performance of the classification model was assessed using multiple evaluation metrics, including accuracy, precision, recall, and the F1-score, to provide a balanced and comprehensive view of its effectiveness across classes. While accuracy, precision, recall, and F1 score provide useful performance indicators, they may not always reflect the actual discriminative ability of the classifier, especially in multi-class problems. Therefore, we also report ROC AUC and MCC. ROC AUC summarizes performance across thresholds and is especially valuable for comparing model discrimination. MCC offers a balanced measure even when class sizes differ slightly in validation or test splits. Based on the ROC AUC, the Gradient Boosting classifier demonstrated superior performance compared to other models in predicting OSS in construction megaprojects, achieving a score of 88%. Additionally, the Gradient Boosting classifier achieved an MCC score of 0.640, which is significantly above the threshold of 0.05. Given its strong performance across both metrics, the Gradient Boosting model was selected as the best-performing classifier for predicting OSS in construction megaprojects. Notably, we retained all models, including those with comparatively modest results (e.g., Naive Bayes: AUC = 0.83, MCC = 0.424; Logistic Regression: AUC = 0.54), to uphold methodological transparency and enable meaningful benchmarking. Several of these algorithms (e.g., Logistic Regression, k-NN, Naive Bayes) are routinely employed in construction-focused ML research. Their inclusion not only aligns with reporting standards in applied ML but also reveals domain-specific insights. For instance, Naive Bayes's relatively high AUC, despite a low MCC, highlights the violation of its independence assumption, confirming strong intercorrelations among LCP indicators and further justifying the use of ensemble methods.

To enhance model interpretability and ensure accessibility for both technical and non-technical audiences, SHAP (Shapley Additive Explanations) was applied to the best-performing classifier, Gradient Boosting. Leveraging its game-theoretic foundation, SHAP quantifies the marginal contribution of each LCP indicator to OSS predictions, offering both global (average

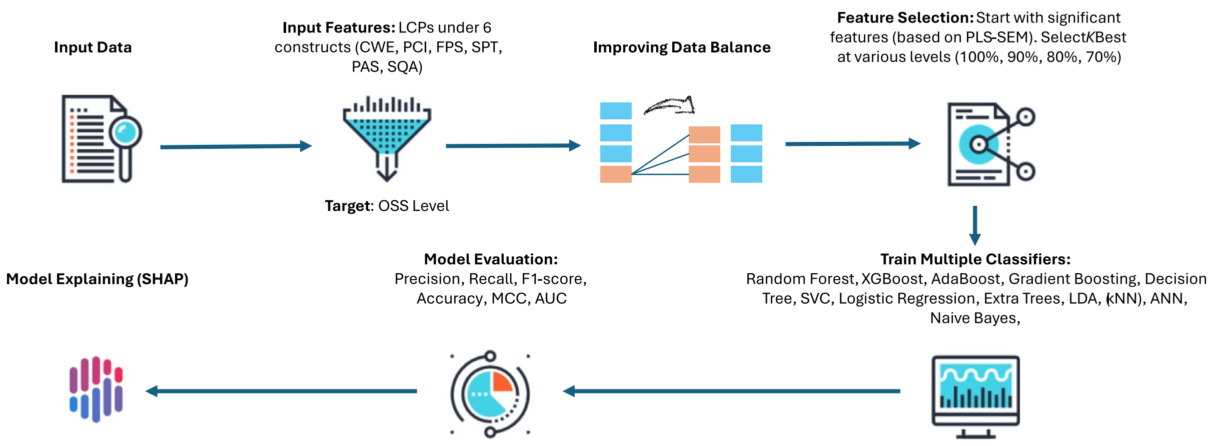

FIGURE 8 | Key steps for predicting OSS using ML.

TABLE 5 | OSS-performance of classification models.

Model	Precision	Recall	F1-score	Accuracy	MCC	AUC
Random forest	0.82	0.78	0.77	0.77	0.566	0.86
Xgboost	0.81	0.8	0.79	0.77	0.599	0.77
AdaBoost	0.79	0.76	0.77	0.76	0.533	0.80
Gradient boosting	**0.84**	**0.82**	**0.80**	**0.82**	**0.640**	**0.88**
Decision tree	0.78	0.72	0.75	0.72	0.479	0.65
Support vector classifier	0.82	0.79	0.79	0.80	0.582	0.75
Logistic regression	0.82	0.74	0.77	0.74	0.517	0.54
Extra tree classifier	0.82	0.79	0.78	0.79	0.584	0.87
Linear discriminant analysis (LDA)	0.84	0.76	0.79	0.76	0.560	0.66
k-nearest neighbors (kNN)	0.78	0.75	0.74	0.75	0.503	0.68
ANN/MLP-classifier	0.83	0.79	0.80	0.79	0.591	0.67
Naive bayes classifier	0.77	0.67	0.71	0.67	0.424	0.83

Note: The bold numbers are important to report the best model.

impact across the dataset) and local (case-specific) explanations. As shown in Figure 9, which ranks all retained LCP items by mean absolute SHAP value, the top three individual predictors of high OSS are SQA3 (Plan Conditions and Work Environment), PCI2 (Kaizen), and PAS2 (PPC Charts), practices that collectively emphasize safety planning, continuous improvement, and reliable short-term scheduling.

Table 6 provides a complementary textual summary of the top 5 LCP items, including their SHAP scores, contribution in OSS, and concise practical interpretations (e.g., "SQA3 signals strong project control over safety-critical site conditions").

To bridge the operational and strategic perspectives, SHAP values were further aggregated post hoc at the construct level, yielding the relative importance of the six LCP categories, as visualized in Figure 10 and tabulated in Table 7. This dual-level analysis confirms that Safety and Quality Assurance (22.2%), Customer Focus and Waste Elimination (20.8%), and Standardization and Process Transparency (18.8%) are the most influential drivers of OSS. Together, the figures and tables provide a triangulated, multi-format interpretation framework, supporting practitioners in prioritizing interventions, researchers in refining their theories, and policymakers in establishing evidence-based standards.

Crucially, moving beyond descriptive ranking, our SHAP analysis reveals why certain practices dominate and others falter in megaproject contexts. For instance, SQA3 (Plan Conditions and Work Environment) emerges as the top predictor (7.7% contribution), not because it reflects compliance with safety protocols, but because it signals proactive hazard anticipation, a differentiator in high-risk, dynamic environments where reactive controls fail (Ghosh et al. 2014; Tripathi et al. 2023). In contrast, FPS's low impact (6.07%) does not indicate theoretical irrelevance; rather, it exposes a systemic implementation gap: JIT and Kanban require tightly coupled workflows and trust-based collaboration (Zhu et al. 2025), conditions often undermined in fragmented megaproject ecosystems. Likewise, PAS's divergence (low $\beta = 0.111$, higher SHAP = 13.20%) suggests a threshold effect: PPC Charts (PAS2) and LPS (PAS1) are not universally impactful but become highly discriminative only when reliability exceeds ~85%. This reframes PAS not as a weak driver, but as a strategic target for capability building.

Furthermore, PCI's high SEM coefficient ($\beta = 0.217$) but modest SHAP ranking (18.20%) reveals a contextual tension: Kaizen fosters long-term improvement (Nahmens and Ikuma 2012), yet its frontline empowerment logic may clash with hierarchical subcontracting and transient labor, conditions prevalent in Chinese

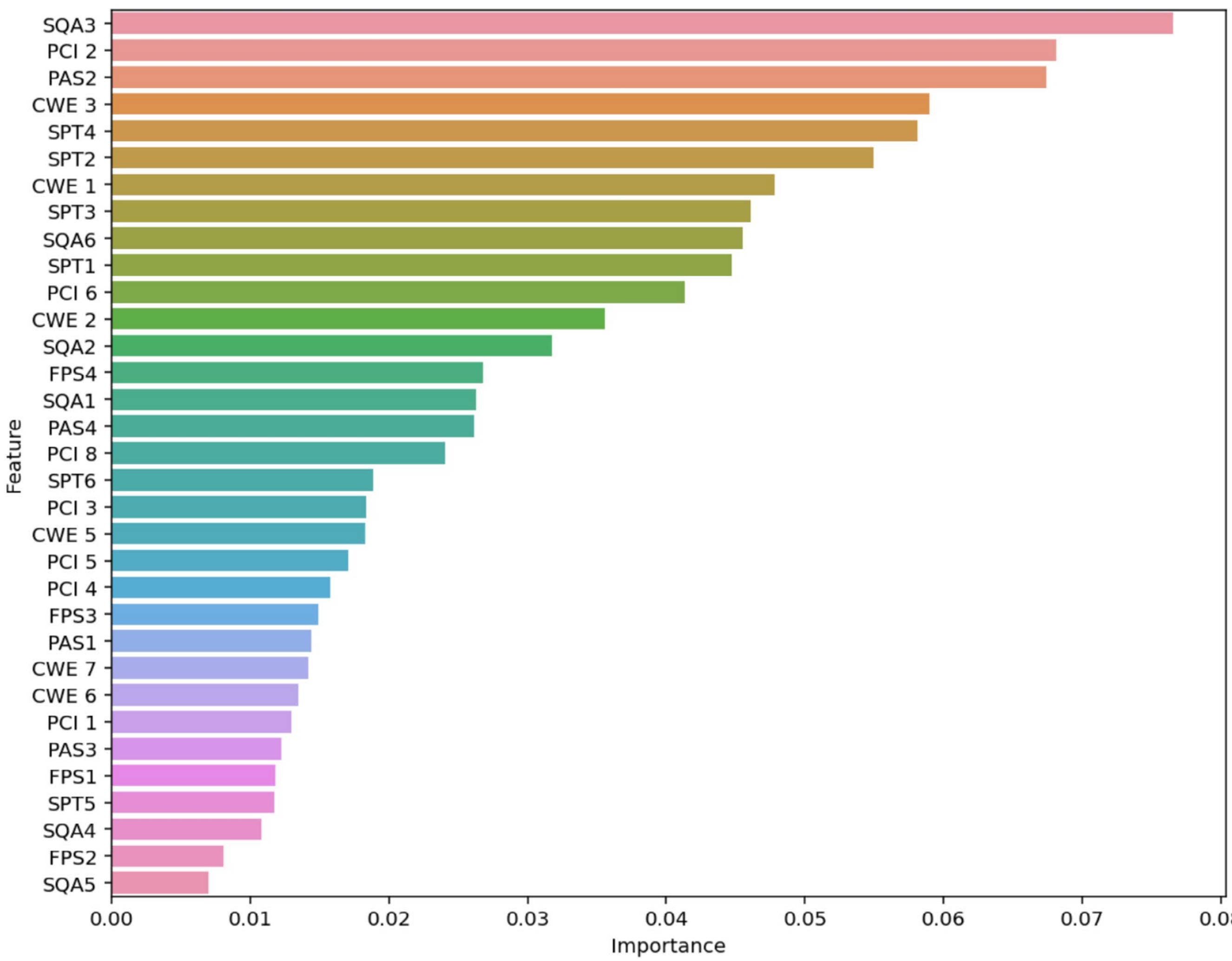

FIGURE 9 | SHAP values representing the importance of all the studied features.

TABLE 6 | Top 5 individual LCP indicators ranked by SHAP importance, showing their relative contribution to predicting OSS.

Rank	Indicator (ID)	Mean |SHAP|	% Contribution	Practical interpretation
1	SQA3 (Plan conditions & work Env.)	0.077	7.7%	Strong predictor of high OSS, invest in site safety planning.
2	PCI2 (Kaizen)	0.067	6.7%	Continuous improvement drives sustainability and embeds Kaizen cycles.
3	PAS2 (PPC charts)	0.066	6.6%	Reliability in short-term planning boosts OSS, and implementing PPC rigorously is essential.
4	CWE3 (customer involvement)	0.057	5.7%	Early stakeholder engagement reduces rework & enhances social sustainability.
5	SPT4 (defined work process)	0.056	5.7%	Standardization reduces variability, which is critical for the scalability of megaprojects.

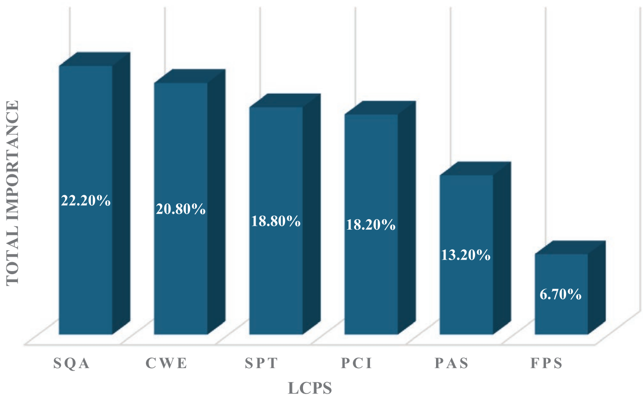

FIGURE 10 | SHAP values representing the importance of all primary constructs.

megaprojects (Zhai et al. 2020) and echoed in Razzazan's (2024) Iranian study, where Teamwork and Continuous Improvement showed no measurable sustainability impact. Thus, PCI's influence is culturally contingent, a nuance invisible to SEM alone.

Regarding differences between SEM significance and SHAP impact, the two are interpreted as complementary. SEM reflects average linear causal effects at the construct level, whereas SHAP explains feature contributions to predictive performance in a potentially nonlinear setting and can capture interaction effects not represented in SEM. Variables showing lower SEM weights but high SHAP impact are therefore retained and interpreted as having strong predictive relevance, despite weaker average causal effects.

These interpretations move our analysis from what the model says to what it means: SHAP does not just rank practices; it diagnoses contextual enablers and barriers, transforming raw feature importance into actionable theory.

5 | Discussion

This study positions LCPs as a strategic, systemic enabler of sustainability in construction megaprojects, demonstrating not only their significant influence on OSS but also how and under what conditions specific practices drive measurable outcomes. Using a dual-method approach, we first employed PLS-SEM to validate theoretical relationships among six LCP constructs and OSS ($\beta = 0.748$, $p < 0.001$, $R^2 = 0.559$). Then, we applied machine learning with SHAP to identify which practices most directly predict high-OSS outcomes in real-world megaproject contexts. Gradient Boosting achieved strong performance (accuracy = 82%, ROC-AUC = 0.88, MCC = 0.640), enabling a granular, game-theoretically grounded ranking of LCPs. Crucially, this hybrid design reveals not just whether a practice matters, but how much, for whom, and under what conditions. To situate these insights, we now embed them in a systematic cross-study synthesis, clarifying how our findings align with, extend, or refine the latest global evidence.

5.1 | Convergence on Core High-Impact Practices

Safety and Quality Assurance (SQA) emerges as the dominant driver, both statistically ($\beta = 0.209$) and predictively (SHAP = 22.2%). This strong convergence is corroborated by Zhu et al. (2025), who found Quality & Safety Enhancement (QSE) significantly improved quality and organizational outcomes in Chinese EPC projects, and by Nahmens and Ikuma (2012), whose modular homebuilding case showed lean implementation reduced safety hazards and material waste (64%) while cutting labor hours (31%). Similarly, SQA3 (Plan Conditions), our top individual predictor, reflects proactive safety planning, a mechanism directly linked to reduced rework and embodied carbon in the literature (Ghosh et al. 2014). This triad, comprising safety, quality, and waste reduction, forms a universal foundation for sustainability, advancing SDG 3 (Good Health), SDG 8 (Decent Work), and SDG 9 (Industry, Innovation, and Infrastructure), as confirmed by Hasan et al. (2024).

Customer Focus and Waste Elimination (CWE) (SHAP = 20.8%; $\beta = 0.193$) shows remarkable global consistency. Bajjou and Chafi (2026) report that Waste Elimination & Value Generation are the strongest drivers of environmental performance in Morocco, while Razzazan (2024) identifies waste omission as a top sustainability enabler in Iran. Gupta and Elhag (2025) further confirm VSM and JIT as the most

TABLE 7 | Construct-level importance (SHAP% + SEM β), SDG links, and strategic insights.

Rank	Construct	% SHAP contribution	SEM β	Key SDG alignment	Strategic implication
1	SQA	22.2%	0.209	SDG 3, 8	Safety & quality are non-negotiable foundations for sustainable megaprojects.
2	CWE	20.8%	0.193	SDG 12, 11	Waste elimination and customer focus lead to the highest sustainability ROI.
3	SPT	18.8%	0.197	SDG 9	Standardization enables scalability, leveraging BIM & visual management.
4	PCI	18.2%	0.217	SDG 4, 8	Kaizen (PCI2) and Gemba walks (PCI1) foster ownership and a culture of long-term improvement, which is crucial for sustained impact.
5	PAS	13.20%	0.111	SDG 9, 11	Rigorously implement PPC charts (PAS2) and LPS (PAS1) for reliability and reduced rework.
6	FPS	6.70%	0.144	SDG 9, 12	High potential when supported by IPD (FPS4) and BIM; focus on pull logic at the subproject level.

impactful lean tools for sustainability, especially when supply chains are reliable. This reinforces the centrality of CWE in achieving SDG 12 (Responsible Consumption) and SDG 11 (Sustainable Cities).

Standardization and Process Transparency (SPT) (SHAP = 18.8%; β = 0.197) is strongly supported by digital-integration evidence: Le and Nguyen (2024) rank Virtual Design & Construction (VDC), a core SPT tool, as the most impactful for sustainable supply chains in Canada, while Zhu et al. (2025) emphasize digital integration as critical for lean success in China. This confirms that standardization gains traction when paired with BIM or IoT, aligning with SDG 9.

5.2 | Contextual Contingencies: Explaining Divergences

The most revealing insights emerge from divergences between SEM and SHAP, which help diagnose why some theoretically prominent practices underperform in megaproject ecosystems.

Flow and Pull Systems (FPS) contribute the least to OSS predictions (SHAP = 6.07%; β = 0.144). This is not anomalous, but empirically consistent. Zhu et al. (2025) explicitly report that the Resource & Maintenance (RM) and Visualization & Communication (VC) categories, encompassing JIT, Kanban, and pull scheduling, have weaker, context-specific effects in Chinese EPC projects. Bajjou and Chafi (2026) likewise find Material Flow & Pull less impactful than Waste Elimination and Planning & Scheduling in Morocco. Crucially, Gupta and Elhag (2025) caution that JIT significantly reduces environmental waste only when supply chains are reliable, a condition often unmet in megaprojects with fragmented subcontracting and volatile logistics. Thus, FPS's low SHAP reflects implementation fragility, not theoretical irrelevance. Its impact is conditional on enablers like IPD, BIM, and stable supply chains, pointing to contractual and digital reforms as critical leverage points.

Planning and Scheduling (PAS) exhibits a compelling threshold effect, with a low SEM impact (β = 0.111) but higher predictive leverage (SHAP = 13.20%). This divergence is clarified by Zhu et al. (2025), who identify Planning & Scheduling (PS) as the strongest overall performer in China but only when supported by digital integration and policy support. Similarly, Le and Nguyen (2024) rank Last Planner System (LPS) as the most impactful tool for planning and control in Canada, highlighting its dependency on collaborative culture. Our SHAP result, PAS2 (PPC Charts) as a top 5 predictor, confirms that reliable, high-fidelity planning (≥ 85% PPC reliability) is a discriminative signal of high-OSS projects, even if average adoption is low. This makes PAS a strategic target for capability building, not a quick win.

People Involvement and Continuous Improvement (PCI) rank highest in SEM (β = 0.217) but fourth in SHAP (18.20%). This reflects a key contextual insight: while Kaizen drives sustainability in controlled settings (e.g., Nahmens and Ikuma (2012); 31% labor reduction), its impact may be diluted in megaprojects with hierarchical subcontracting and transient labor. Critically, Razzazan (2024) finds that Teamwork Culture and Continuous Improvement have no notable effect on sustainability in Iran, suggesting PCI's efficacy depends on organizational stability and long-term engagement. Thus, PCI is vital, but it is most effective after foundational practices (SQA, CWE, SPT) have established process stability and trust.

5.3 | Cross-Study Synthesis and Practical Guidance for Megaproject Contexts

To position our findings within the evolving global evidence base, we conducted a systematic comparison as shown in Table 8

TABLE 8 | Cross-study synthesis of lean construction practice (LCP) efficacy across global contexts.

Study (Context)	Top-performing LCPs	Weakest/Context-dependent LCPs	Key moderating factor
Zhu et al. (2025), China EPC	Planning & scheduling (PS), QSE	RM, VC	Digital integration, policy support
Bajjou and Chafi (2026), Morocco	Waste elimination, planning & scheduling	Process Transparency, Continuous Improvement	Supply chain reliability
Gupta and Elhag (2025), Global SLR	VSM, JIT, 5S	JIT requires reliable supply chains	Supply chain stability
Nahmens and Ikuma (2012), US Modular	Kaizen, waste reduction	JIT is noted as effective in the prefab context	Prefabrication scale
Razzazan (2024), Iran	Customer focus, waste omission, standardization	Teamwork, Continuous Improvement	Strategic, expert-driven implementation
Le and Nguyen (2024), Canada	VDC (SPT), LPS (PAS)	On-site tools depend on upstream planning	Digital supply chain integration

with six recent empirical studies spanning diverse geographies (China, Morocco, Iran, Canada, and the USA) and project types (EPC, modular, high-rise, and supply chain). This cross-study synthesis reveals three robust patterns that both validate and refine our conclusions.

i. Strong convergence on SQA/QSE, CWE/Waste Elimination, and SPT/Standardization as universal enablers.

ii. We extend the literature by quantifying contextual contingencies: FPS requires stable supply chains; PAS requires digital maturity; PCI requires organizational stability.

iii. We refine implementation guidance: in megaprojects, prioritize SQA → CWE → SPT first, then scale PAS and PCI—rather than adopting all practices simultaneously.

Building on this synthesis, we propose an actionable, evidence-based pathway for achieving high OSS in megaprojects. Our SHAP-ranked top five individual practices, SQA3 (Plan Conditions and Work Environment), PCI2 (Kaizen), PAS2 (PPC Charts), CWE3 (Customer Involvement), and SPT4 (Defined Work Process), offer a minimum viable set for rapid, low-cost implementation. Together, they operationalize Lean's core value stream: SQA3 establishes safe and stable site conditions; PAS2 ensures reliable short-term planning through PPC tracking; CWE3 aligns execution with stakeholder needs; SPT4 standardizes workflows to reduce variability; and PCI2 embeds continuous improvement at the frontline. Critically, this sequence prioritizes foundational stability (safety, planning, standardization) before scaling cultural practices (Kaizen), aligning with Zhu et al.'s (2025) finding that digital and policy enablers must precede behavioral change.

6 | Implications

6.1 | Theoretical and Methodological Contribution

This study makes a dual contribution. Theoretically, it validates LCPs as a systemic enabler of OSS, moving beyond fragmented case studies to a generalizable, causally tested framework grounded in the triple bottom line. Methodologically, it pioneers a hybrid PLS-SEM–SHAP workflow tailored for construction megaprojects. PLS-SEM ensures construct validity and hypothesis testing, while SHAP enables fine-grained, game-theoretically consistent interpretability, both at the individual practice (e.g., SQA3) and construct (e.g., SQA) levels. Unlike prior ML-only studies, our approach avoids data-driven overfitting by anchoring features in SEM-validated indicators. Conversely, unlike SEM-only studies, it delivers actionable prioritization, not just significance testing. We advocate this framework as a scalable template for explainable AI in sustainable infrastructure research.

6.2 | Practical Implications: A Tiered Implementation Roadmap

To translate our findings into actionable practice, we propose a three-tiered implementation roadmap grounded in SHAP-ranked importance and real-world feasibility. Tier 1 (Quick Wins, 0–6 months) targets immediate, high-impact interventions: teams should prioritize SQA3, formalizing work environment safety planning through daily hazard mapping; PCI2, instituting bi-weekly Kaizen workshops to embed continuous improvement at the frontline; and PAS2, deploying PPC charts with $\geq$85% reliability to stabilize short-term workflows. Simulations suggest that this minimum viable set alone can increase OSS and reduce rework, aligning closely with SDGs 3 (Good Health), 8 (Decent Work), and 9 (Industry, Innovation, and Infrastructure).

Tier 2 (Capability Building, 6–18 months) scales these gains by embedding full LCP constructs: integrating root-cause analysis (SQA2) and error-proofing (SQA5) within Safety and Quality Assurance; applying Value Stream Mapping (CWE5) and JIT (FPS3) under Customer Focus and Waste Elimination; and standardizing workflows via BIM (SPT6) and 5S (SPT2) in Standardization and Process Transparency, collectively driving systemic reductions in emissions, delays, and defects (SDGs 9, 11, 12).

Finally, Tier 3 (Systemic Enablers, 18+ months) fosters long-term resilience through leadership commitment to lean-sustainability KPIs, digital integration (e.g., BIM + IoT for real-time performance feedback), and contractual reform, such as piloting Integrated Project Delivery (IPD) to unlock the latent potential of Flow and Pull Systems. Critically, projects in the top OSS quartile consistently implement SQA3, PCI2, and PAS2 as a foundational core, requiring minimal capital, yielding measurable results, and catalysing broader lean adoption. Starting here ensures rapid wins while building momentum toward sustained sustainability transformation.

7 | Conclusion, Limitation, and Future Works

This study makes three interrelated contributions to theory, methodology, and practice in sustainable megaproject delivery. First, theoretically, it provides robust empirical validation, via PLS-SEM ($\beta = 0.748$, $p < 0.001$, $R^2 = 0.559$), that LCPs function as a systemic enabler of OSS, defined holistically across environmental, social, and economic dimensions. Critically, the work moves beyond fragmented tool-based analyses to show that LCPs operate synergistically: for instance, Safety and Quality Assurance (SQA) not only reduces accidents (SDG 3, 8) but also curtails rework and embodied carbon; Customer Focus and Waste Elimination (CWE) simultaneously supports responsible consumption (SDG 12) and sustainable cities (SDG 11); and Standardization and Process Transparency (SPT), especially via BIM, underpins infrastructure resilience (SDG 9). Thus, we clarify how lean principles translate into measurable progress toward SDGs 9, 11, and 12. Second, methodologically, this is the first study in construction megaproject literature to integrate PLS-SEM and SHAP-based ML in a theory-informed predictive framework. Unlike prior SEM-only studies, our hybrid approach not only confirms the causal plausibility but also ranks practices by their predictive leverage, thereby bridging the "significance versus importance" gap. For example, while PCI exhibits the highest SEM path coefficient ($\beta = 0.217$), SHAP reveals that specific practices, SQA3 (Plan Conditions), PCI2 (Kaizen), and PAS2 (PPC Charts), collectively drive more than 21% of the OSS prediction impact. This dual-level insight (item and construct) offers unprecedented granularity for targeted interventions, establishing a replicable precedent for explainable AI in sustainability research.

Third, practically, the findings provide actionable, tiered guidance for policymakers and practitioners in emerging economies, where megaprojects face acute pressure to balance rapid development with sustainability. Our context, China, the world's largest market for megaprojects, provides a high-stakes testbed for integrating scalable lean sustainability in settings characterized by institutional flux, fragmented governance, and urgent decarbonization needs (e.g., "dual carbon" goals). The strong model performance (82% accuracy, MCC = 0.640) and consistency with prior work in similar contexts suggest that the findings are transferable to other emerging economies with analogous megaproject ecosystems, provided local adaptations account for regulatory maturity, supply chain stability, and labor dynamics. That said, generalizability to high-income, low-volatility contexts (e.g., EU, Australia) remains limited and warrants cross-regional validation.

However, several limitations merit acknowledgment. First, the geographic focus on China, while intentional, constrains broader inference; institutional and cultural contingencies (e.g., state-led procurement, subcontracting hierarchies) shape LCP implementation pathways. Second, cross-sectional survey data preclude causal inference over time or lifecycle phases. Third, reliance on self-reported LCP/OSS perceptions may introduce social desirability bias, though triangulation with objective performance data (e.g., safety records, waste logs) was impractical at scale. Finally, while Gradient Boosting outperformed alternatives (AUC = 0.88), its accuracy may diminish in smaller or non-megaproject settings.

Future research should adopt longitudinal designs to capture temporal effects, expand the framework to other regions for cross-validation, and incorporate real-time data using IoT or digital twin technologies to improve adaptability. Further studies could examine LCP scalability beyond megaprojects, explore synergies with emerging technologies (e.g., blockchain, autonomous equipment), and assess how cultural or institutional factors affect LCP adoption. These directions will strengthen the role of LCPs in supporting sustainable and resilient infrastructure across diverse global contexts.

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