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A Maturity Assessment Framework for Smart Logistics Parks: Distinctions from Traditional Models and Implications for Transformation

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Abstract

Smart logistics parks (SLPs) drive modern economies and global supply chains, making maturity assessment essential for guiding investment, improvement and strategic decision-making. Existing maturity assessment models for traditional logistics parks (TLPs) overlook the distinctive advancements of SLPs, underscoring the need for specialized frameworks. In this study, an SLP maturity evaluation model was developed that differentiates SLPs from TLPs assessments to support smart logistics transformation. The framework comprises five core dimensions with 20 sub-factors: Smart Economy, Public Services and Smart Governance, Smart Infrastructure and Intelligent Technology Application, Skilled Human Capital, and Environmental Sustainability. This structure was validated through a literature review and expert input. For comparison, the TLPs model is based on China's national standard. Using the Analytic Hierarchy Process (AHP) to determine factor importance, results indicate that SLPs prioritize Smart Infrastructure and Intelligent Technology Application (0.3229), followed by Public Services and Smart Governance (0.2447). In contrast, TLPs place the highest emphasis on Service Capability and Operation Management (0.3317). While both models value infrastructure, operational services, and environmental considerations, SLPs place stronger emphasis on technological innovation and digital governance, whereas TLPs focus on operational efficiency and service quality. These findings confirm that although infrastructure and operations remain central to both, transitioning to SLPs demands a greater focus on intelligent technology. This study provides empirical evidence that the SLPs' transformation necessitates the integration of intelligent systems while simultaneously maintaining efficiency, service quality, and sustainability. This research offers practical guidance for investors, policymakers, and operators.

Keywords: Smart Logistics Parks, Maturity Assessment Framework, Traditional Logistics Parks, Digital Transformation, AHP

Introduction

Smart logistics parks (SLPs) are advanced hubs that use IoT, AI, big data, and automation to optimize warehousing, transportation, and distribution (Shang & Li, 2021; Wei & Wang, 2021). Leveraging these technologies, SLPs drive economic growth, industrial upgrading, and environmental sustainability while fostering service innovation and operational efficiency (Lv et al., 2020). Their adoption is accelerating worldwide. Germany's Duisburg Intermodal Terminal employs IoT and AI to optimize intermodal transport (Romano & Taube, 2022). Singapore's Jurong Logistics Hub integrates autonomous vehicles, AI-driven inventory systems, and digital twins (Ferro-Escobar et al., 2022). In the U.S., providers such as Amazon and UPS deploy robotics and predictive analytics (Andiyappillai, 2021). Elsewhere, Dubai's Logistics District incorporates blockchain and real-time tracking (Issac, 2024). Even in emerging economies such as Brazil and Kenya, digital solutions are being piloted in logistics corridors to enhance transparency and reduce congestion (Gbahabo & Afful-Mensah, 2024). Collectively, these developments reflect a global shift toward intelligent, sustainable, and resilient logistics networks shaped by digital transformation and strategic policy initiatives.

Traditional logistics parks (TLPs) perform essential logistics functions but are labor-intensive, relying on physical infrastructure and manual processes such as warehouse management, tracking, and documentation, with minimal automation. In contrast, SLPs achieve these functions through advanced technologies, including predictive analytics, automated control systems, and real-time route optimization, thereby enhancing coordination and responsiveness (Lv et al., 2020). SLPs emphasize sustainability by reducing environmental impact, optimizing resource utilization, and contributing to long-term socio-economic development (Sun et al., 2024). This transition is essential for establishing efficient and adaptive logistics networks capable of maintaining resilience with a digitally transformed, sustainability-oriented economy (Agnieszka et al., 2021).

Despite their increasing importance, structured frameworks for systematically developing and evaluating SLPs remain limited (Pereira et al., 2023). Without such frameworks, organizations and policymakers lack clear guidance on assessing the degree of smart transformation and aligning it with strategic objectives (Elpida et al., 2022). TLPs benefit from established evaluation frameworks, such as the Performance Evaluation Model (PEM) defined by the National Standardization Administration (2018). However, previous research on smart logistics has not yielded a dedicated maturity model for parks, focusing instead on broader city logistics or specific technologies (Tran-Dang, 2025; Woschank, 2020).

Consequently, a clear gap exists for a specialized framework to assess and guide the smart transformation of logistics parks. This study bridges that gap by developing a comparative and descriptive maturity assessment framework tailored for SLPs, which systematically contrasts with traditional models to illuminate the necessary strategic shifts.

The proposed framework is *descriptive* in its identification of core SLPs dimensions and sub-factors, and *comparative* in its systematic contrast with the TLPs model. Its structure is theoretically grounded in the Capability Maturity Model (CMM) tradition. This research focused on establishing this foundational framework, developing a full *prescriptive* model with defined maturity levels as a designated goal for future work.

The primary contributions of this research are threefold:

- A novel SLPs assessment framework: A dedicated multidimensional framework for assessing SLPs, is proposed and validated, moving beyond the limitations of traditional models.
- A comparative analysis for transformation: A systematic comparative analysis with TLPs is provided that clearly identifies the strategic priorities and critical focus areas required for smart transformation.
- A theoretically grounded foundation: A theoretically informed foundation, rooted in CMM principles, is offered for future development of a full maturity model and practical strategic planning.

This study thus provides stakeholders with a tool to support their transition from TLPs to SLPs, offering clear guidance on technology upgrades and targeted development priorities.

Materials and Methods

Dimensions of Intelligent Development in Smart Logistics Parks

SLPs represent advanced information and communication technology (ICT) applications within the smart city paradigm, yet lack a standardized development framework (Elpida et al., 2022). Accordingly, leveraging the developmental experiences of smart cities and smart parks offers guidance for advancing SLP practices (Mehmood et al., 2024). Some core dimensions underpinning the intelligent evolution of SLPs were identified from the literature. Skilled human capital emphasizes talent development, innovation capacity, and community engagement, reflecting the availability of qualified personnel for intelligent logistics (Kirimtat et al., 2020). Smart infrastructure highlights the role of ICT, IoT, and data storage in building digital foundations for SLPs (Bibri, 2020). Intelligent technology application enhances logistics operations through cloud computing, big data analytics, and AI (Lv et al., 2020). Public services focus on planning, ecological development, and operational efficiency (Ahad et al., 2020). Smart governance addresses policy, management, and collaboration, effectively reflecting managerial capabilities of SLPs (Bibri, 2020). Smart economy considers financial performance and economic outcomes, including financial management, innovative business models, and transport cost optimization (Kirimtat et al., 2020). Finally, environmental sustainability promotes green logistics, carbon reduction, renewable energy, and eco-friendly practices to ensure long-term resilience (Ahad et al., 2020).

These dimensions form a reinforcing cycle: human capital drives technological innovation, which enhances infrastructure and services, improves financial outcomes, and enables reinvestment in continuous improvement (Suresh et al., 2024).

Content Validation Using IOC and CVR Methods

In this study, factor validation for assessing SLPs' maturity was conducted through expert evaluation for factors initially derived from secondary data. Two recognized methods, Item-Objective Congruence (IOC) and Content Validity Ratio (CVR), were employed to assess content validity in research instruments (Rusticus, 2023). IOC gauges the correspondence between individual items and specific objectives by analyzing expert judgments (Agah et al., 2024). Using a scoring scale of -1, 0, and +1 to denote disagreement, neutrality, and agreement, respectively, a high IOC score indicates strong content validity (Chatprem et al., 2020). CVR, introduced by Lawshe (1975), is a measure of an item's necessity based on expert ratings. It is calculated from the proportion of experts who rate the item as essential (Rusticus, 2023). Higher CVR values denote stronger relevance, with the minimum required value contingent upon the total number of evaluators (Marcela et al., 2023).

Previous research highlights the effectiveness of IOC and CVR in ensuring measurement precision. For example, IOC has been used in education to refine questionnaires (Yusoff et al., 2021), while the CVR has validated diagnostic survey items within clinical research (Mary, P. et al., 2024). Such evidence demonstrates that both methods strengthen content validity through structured expert review, producing reliable and valid instruments. Both IOC and CVR were jointly in the study to refine survey items, ensuring they align with research objectives and reflect expert consensus. IOC assesses how effectively each item captures the intended construct, whereas CVR evaluates its necessity. The combined application of these methods improves the validity and reliability of the measurement instrument, minimizes ambiguity, and enhances the overall quality of data collection (Rusticus, 2023).

Analytic Hierarchy Process (AHP) and its application

The Analytic Hierarchy Process (AHP) provides a structured framework for decomposing complex problems into hierarchical criteria through pairwise comparisons (Maretto et al., 2022). This method transforms expert judgments into weighted priorities, effectively integrating both qualitative and quantitative inputs while reducing decision-making subjectivity (Chaube et al., 2024).

Mathematically, AHP constructs a pairwise comparison matrix $A=[a_{ij}]$, following Saaty's 1-9 scale, where $a_{ij}=1/a_{ji}$. The relative weights, w, are derived as the principal eigenvector satisfying $Aw=\lambda_{max}w$. A Consistency Ratio (CR) below 0.10 confirms judgment reliability, calculated as $CR=CI/RI$, where the Consistency Index $(CI)=(\lambda_{max}-n)/(n-1)$ (Maretto et al., 2022).

AHP is particularly suitable for assessing SLPs' maturity, where established quantitative data remains limited. While its structured approach facilitates complex problem decomposition and consistency verification, the method faces limitations, including cognitive biases, rank reversal phenomena, and respondent burden with numerous comparisons (Chaube et al., 2024). Future research could integrate AHP with other methods, such as fuzzy logic, to handle uncertainty in judgments, thereby overcoming the inherent limitations of a single tool (Janmontree et al., 2025).

In logistics and supply chain contexts, AHP has demonstrated utility in supplier selection, facility location, and risk assessment by balancing multiple criteria such as cost, sustainability, and operational efficiency. For example, it enables supplier evaluation based on criteria such as cost, quality, delivery reliability, and sustainability (Galal et al., 2025). Janmontree et al. (2025) integrated AHP with other methods to develop a robust hybrid Multi-Criteria Decision Analysis (MCDA) framework that addresses the complex and uncertain challenges of supplier selection. In logistics operations, AHP supports decisions on distribution strategies and facility siting by balancing infrastructure capacity, environmental considerations, and operational costs (Tepic et al., 2025). These applications demonstrate their value in supporting complex, multi-criteria decisions across supply chains (Moslem et al., 2023). Specifically for maturity assessment, the AHP facilitates priority identification and strategy formulation through the systematic ranking of factors and the integration of expert perspectives (Sarker & Klungseth, 2024; Verma & Rastogi, 2024).

Study process design

The study follows a structured, three-stage process: framework development, weight assignment, and result comparison and discussion, as illustrated in Figure 1.

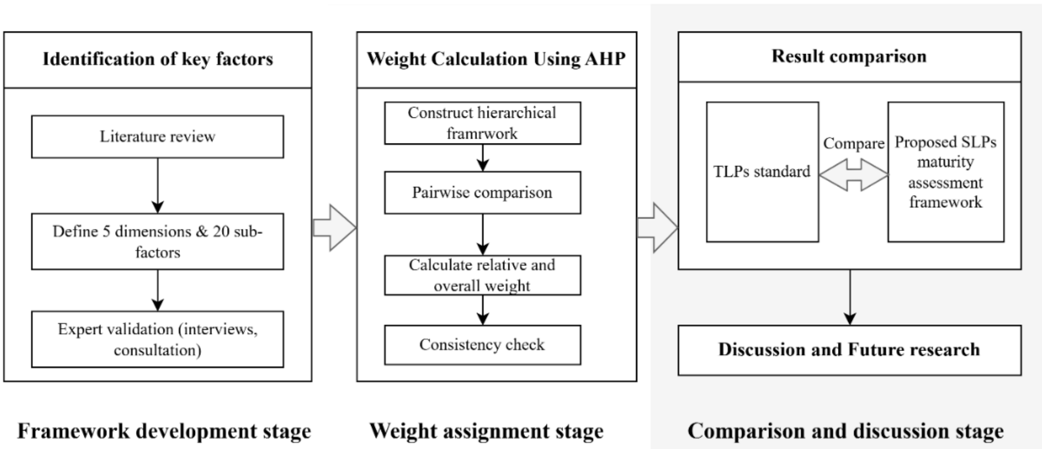

Figure 1 Methodological Framework

Stage 1: Framework Development

The study began by identifying the maturity assessment factors relevant to SLPs. This was achieved through a comprehensive literature review encompassing smart cities, smart parks, and logistics management. Five core dimensions and twenty sub-factors were defined to represent the key capability areas of SLPs. These factors were validated through expert interviews and consultations to ensure their theoretical soundness and practical applicability.

Stage 2: Weight Assignment

The AHP was applied to determine the importance of factors through an hierarchical framework encompassing both dimensions and sub-factors. Experts conducted pairwise comparisons, and the resulting judgments were used to calculate relative and overall weights. All CR confirmed acceptable coherence (CR < 0.10), validating expert judgments (Maretto et al., 2022).

Stage 3: Comparison and Discussion

The proposed SLPs maturity framework was then compared with the TLPs benchmark model, which is based on China's national standard for logistics park evaluation. This comparative analysis identifies structural and priority differences between the two frameworks. The insights gained from this comparison form the basis for the discussion, highlighting implications for guiding the transformation from TLPs to SLPs and proposing future research directions.

The framework established in this study serves as a diagnostic mechanism for evaluating current operational states, with AHP-derived weights revealing strategic priorities. The formalization of maturity levels and progression thresholds constitutes a subsequent research phase, deliberately deferred to maintain the framework's present adaptability while enabling future prescriptive implementation.

The data collection process lasted for three months and involved seven experts (each with over ten years of domain-specific experience) who participated in both the validation and weighting stages. The panel was deliberately composed to incorporate perspectives from academia, industry, and government sectors, ensuring a comprehensive and balanced consensus on maturity factors. While the sample size is limited, it is consistent with common practices in AHP-based research, where depth of expert insight is prioritized over sample breadth (Chaube et al., 2024; Rawat et al., 2022). Experts were selected through purposive sampling to represent key stakeholder groups, thereby enhancing the relevance of the collected input. It should be acknowledged, however, that the exclusive reliance on China-based experts may limit the generalizability of findings to other regional or industrial contexts. The geographical and professional concentration introduces a potential risk of cultural and selection bias (Pant et al., 2025). To mitigate this, the study incorporated experts from diverse sectors and anonymized individual judgments during data aggregation (Zhang & Wu, 2023). Nevertheless, the small sample size precludes rigorous statistical analysis of consensus, and the results should be interpreted as a set of prioritized criteria derived from a qualified yet limited panel. Future research should seek to include international experts and validate the framework across varied logistical settings.

Results

Smart Logistics Parks Maturity Assessment Factors Framework

The maturity assessment framework for SLPs was derived through expert input and systematic screening to ensure factor relevance, practicality, and adaptability. Redundant factors were removed, and only high-validity factors were retained. Specifically, factors below the CVR threshold of 0.99 were excluded, thereby ensuring the precision of the measurement instrument.

The validated framework consists of five core dimensions: Smart Economy (B1), Public Services and Smart Governance (B2), Smart Infrastructure and Intelligent Technology Application (B3), Skilled Human Capital (B4), and Environmental Sustainability (B5). The conceptual structure is outlined in Figure 2, while Table 2 specifies the critical factors and their sub-factors.

Smart Economy (B1) reflects economic performance and efficiency in smart operations, a priority area due to its direct influence on organizational outcomes (Chaopaisarn & Woschank, 2021). Public Services and Smart

Governance (B2) emphasizes improved service delivery and regulatory oversight through digital technologies, promoting industrial synergy and stakeholder satisfaction (Pereira et al., 2023). Smart Infrastructure and Intelligent Technology Application (B3) serves as the operational backbone, enabling digital transformation through advanced technologies and resilient infrastructure (Facchini et al., 2020). Skilled Human Capital (B4) highlights workforce adaptability, innovation, and structured training essential for sustaining smart logistics operations (Feng & Ye, 2021). Environmental Sustainability (B5) covers eco-friendly practices and long-term environmental strategies to reduce ecological impact while maintaining operational efficiency (Brunetti et al., 2024).

The stepwise validation confirms the framework's robustness, ensuring it captures the most critical aspects of SLPs' development. This validated structure serves as the basis for subsequent AHP weighting analysis to determine the relative importance of each dimension and factor.

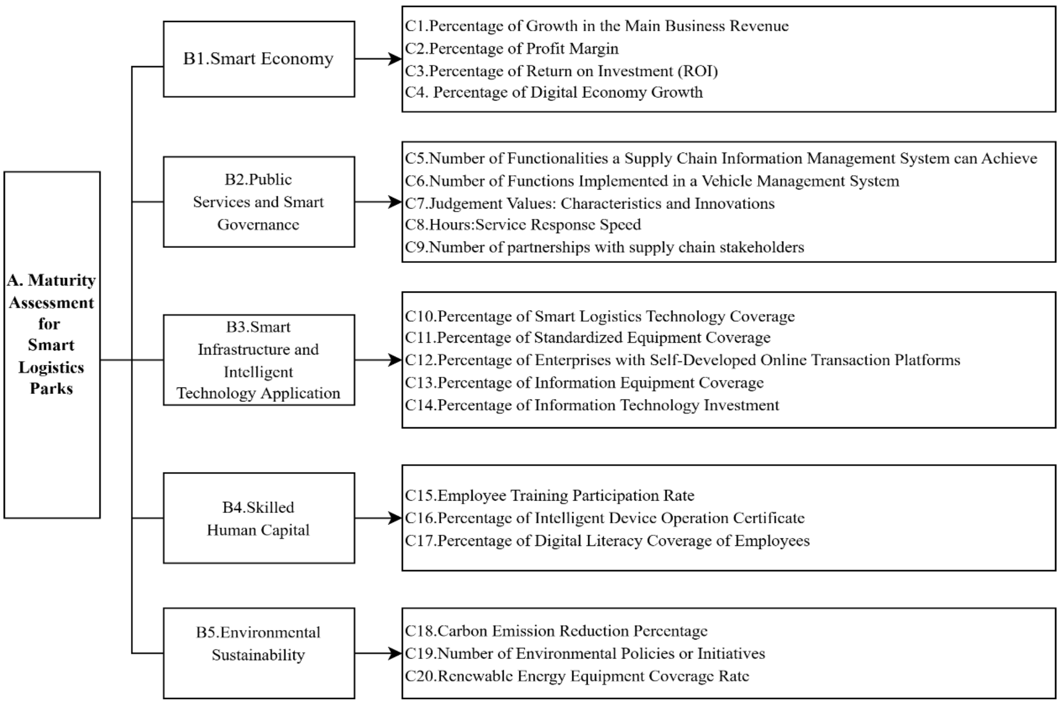

Figure 2 Framework for Maturity Assessment of the SLPs

Table 1 Summary of Critical Factors of Smart Logistics Parks Maturity Assessment Framework

Main Factor	Sub-factor	Description
B1. Smart Economy	C1. Percentage of Growth in the Main Business Revenue	The revenue increases from core activities of SLPs, such as logistics services, warehousing, supply chain management, and digital solutions (Liu et al., 2021).
	C2. Percentage of Profit Margin	Reflects the park's cost control and performance in logistics, warehousing, supply chain management, digitalization, and intelligent services (Jang & Ahn, 2021).
	C3. Percentage of Return on Investment (ROI)	Measures the returns generated from investments in intelligent facilities, technologies, and logistics services (Liu et al., 2021).
	C4. Percentage of Digital Economy Growth	Indicates the growth of the digital economy in areas such as information technology, big data, and artificial intelligence (Sishi & Telukdarie, 2021).

Table 2 (Cont.)

Main Factor	Sub-factor	Description
B2. Public Services and Smart Governance	C5. Number of Functionalities a Supply Chain Information Management System can Achieve	The number of functions or modules that the system can provide contributes to the efficient management and optimization of the supply chain (Weihua Liu et al., 2021).
	C6. Number of Functions Implemented in a Vehicle Management System	The number of system functions or modules designed for managing and optimizing vehicle usage, scheduling, maintenance, and related tasks within the park (Dintén et al., 2023).
	C7. Judgement Values: Characteristics and Innovations	The unique advantages and innovative practices in logistics management, technology application, and operational models within the park (Feng & Ye, 2021).
	C8. Hours: Service Response Speed	The speed at which park management responds to and handles various demands. This factor primarily assesses the park's service capability and efficiency (Xu et al., 2024).
	C9. Number of partnerships with supply chain stakeholders	Indicates the level of ecosystem collaboration and value chain integration (Siems et al., 2023).
B3. Smart Infrastructure and Intelligent Technology Application	C10.Percentage of Smart Logistics Technology Coverage	Reflects the depth and breadth of intelligent logistics technology application in the park, expressed as the ratio of operations using intelligent technology to total logistics operations (Ansari & Ujjan, 2024).
	C11.Percentage of Standardized Equipment Coverage	The number of enterprises in the park that use standardized logistics equipment (Lagorio et al., 2023).
	C12.Percentage of Enterprises with Self-Developed Online Transaction Platforms	The number of enterprises in the park that have developed and operate their platforms with online transaction capabilities (Lagorio et al., 2023).
	C13.Percentage of Information Equipment Coverage	The proportion of deployed information devices in the park relative to its overall needs (Lagorio et al., 2023).
	C14.Percentage of Information Technology Investment	The park's capital investment is in IT infrastructure, digital systems, and intelligent equipment to support digital transformation (Sishi & Telukdarie, 2021).
B4. Skilled Human Capital	C15.Employee Training Participation Rate	The percentage of employees participating in structured training programs related to logistics technologies, intelligent systems, digital tools, or industry-specific competencies (Othman et al., 2022).
	C16.Percentage of Intelligent Device Operation Certificate	The proportion of personnel who have completed professional training and obtained certification for operating smart equipment, relative to the total number of operators (Nwaogu et al., 2024).
	C17.Percentage of Digital Literacy Coverage of Employees	The proportion of employees in a logistics park with specific digital skills and knowledge (Liu & Ye, 2022).
B5. Environmental Sustainability	C18.Carbon Emission Reduction Percentage	The percentage reduction in carbon emissions achieved through governance measures reflects the park's effectiveness in carbon reduction (Dobers et al., 2023).
	C19.Number of Environmental Policies or Initiatives	The number of environmental policies, plans, or projects initiated by the park reflects its commitment to and execution of environmental governance (Tian et al., 2023).
	C20.Renewable Energy Equipment Coverage Rate	The proportion of enterprises in the park using renewable energy equipment reflects the adoption of green energy solutions (Othman et al., 2022).

Weight assignment for the Factors of Maturity Assessment Frameworks

To determine the relative importance of each factor in both SLPs and TLPs, the AHP was applied to each model separately. This section reports the results for SLPs and TLPs independently; the comparative analysis is provided in the discussion section.

(1) Smart Logistics Parks Maturity Assessment Framework

Table 3 shows the AHP-derived weight distribution for the SLPs maturity assessment framework. Among the five main factors, Smart Infrastructure and Intelligent Technology Application (B3) carries the highest weight (0.3229), reflecting its central role in SLPs development. Within this dimension, Smart Logistics Technology Coverage Rate (C10) has the highest overall sub-factor weight (0.1051, ranked 1st), followed by Information Technology Investment Ratio (C14) (0.0796, ranked 2nd). These results highlight the dominant influence of technological innovation and digital infrastructure on SLPs' maturity (Lagorio et al., 2023).

Public Services and Smart Governance (B2) ranks second (0.2447). Its top sub-factor, Functionalities of the Supply Chain Information Management System (C5), weights 0.0706 (ranked 3rd), underscoring its pivotal role in driving digital transformation and optimizing supply chain operations (Weihua Liu et al., 2021).

In Skilled Human Capital (B4), Intelligent Equipment Operation Certification (C16) holds a weight of 0.0693 (ranked 4th), indicating the strategic importance of technically proficient personnel in operating and maintaining smart logistics systems (Nwaogu et al., 2024).

Although Environmental Sustainability (B5) ranks lowest (0.1065), this likely reflects the current developmental focus of SLPs, where establishing technological and operational foundations is perceived by experts as a more immediate priority than comprehensive environmental management. Its top sub-factor—Carbon Emission Reduction Percentage (C18)—is the most influential in this dimension (0.4934). This underscores its importance to environmental performance. In contrast, Renewable Energy Equipment Coverage (C20) receives the lowest weight (0.1958 of B5's weight), potentially due to its higher upfront costs and more indirect contribution to core operational performance metrics in the short term (Tao et al., 2021).

Overall, the top five sub-factors are C10 (Smart Logistics Technology Coverage: 0.1051, C14 (Information Technology Investment: 0.0796), C5 (Supply Chain Information System Functionalities: 0.0706), C16 (Intelligent Device Operation Certificate: 0.0693), and C1 (Growth in Main Business Revenue: 0.0632), aligning with the technological and operational focus of SLPs. Conversely, the lowest-ranked sub-factors—C20 (Renewable Energy Equipment Coverage: 0.0209), C17 (Digital Literacy Coverage: 0.0275), C9 (Supply Chain Partnerships: 0.0307), C3 (Return on Investment: 0.0316), and C19 (Environmental Policies: 0.0331)—currently receive less emphasis but may increase in importance as technological capabilities mature and environmental policies evolve (Lagorio et al., 2023).

These findings confirm that technological integration, digital infrastructure, and skilled workforce development drive SLPs' maturity, while environmental sustainability, though lower in priority, is expected to grow in importance.

Table 3 Weight of Factors for Smart Logistics Parks Maturity Assessment

Main Factor	Weight	Sub-factor	Local Weight	Overall Weight	Ranking of Sub-factor
B1 Smart Economy	0.1854	C1 Percentage of Growth in the Main Business Revenue	0.3407	0.0632	5
		C2 Percentage of Profit Margin	0.2865	0.0531	7
		C3 Percentage of Return on Investment (ROI)	0.1703	0.0316	17
		C4 Percentage of Digital Economy Growth	0.2026	0.0376	14
B2 Public Services and Smart Governance	0.2447	C5 Number of Functionalities a Supply Chain Information Management System can Achieve	0.2886	0.0706	3
		C6 Number of Functions Implemented in a Vehicle Management System	0.1904	0.0466	10
		C7 Judgement values: Characteristics and Innovations	0.2512	0.0615	6
		C8 Hours: Service Response Speed	0.1443	0.0353	15
		C9 Number of partnerships with supply chain stakeholders	0.1255	0.0307	18
B3 Smart Infrastructure and Intelligent Technology Application	0.3229	C10 Percentage of Smart Logistics Technology Coverage	0.3255	0.1051	1
		C11 Percentage of Standardized Equipment Coverage	0.1417	0.0457	11
		C12 Percentage of Proportion of Enterprises with Self-Developed Online Transaction Platforms	0.1233	0.0398	13
		C13 Percentage of Information Equipment Coverage	0.1628	0.0525	8
		C14 Percentage of Information Technology Investment	0.2467	0.0796	2
B4 Skilled Human Capital	0.1405	C15 Employee Training Participation Rate	0.3108	0.0437	12
		C16 Percentage of Intelligent Device Operation Certificate	0.4934	0.0693	4
		C17 Percentage of Digital Literacy Coverage of Employees	0.1958	0.0275	19
B5 Environmental Sustainability	0.1065	C18 Carbon Emission Reduction Percentage	0.4934	0.0525	9
		C19 Number of Environmental Policies or Initiatives	0.3108	0.0331	16
		C20 Renewable Energy Equipment Coverage Rate	0.1958	0.0209	20

(2) Traditional Logistics Parks Performance Evaluation Model

According to the National Standardization Administration (2018), the PEM for TLPs comprises four primary indicators, 18 secondary indicators, and 52 tertiary indicators. **Error! Reference source not found.** presents the PEM factor weights, highlighting the primary indicators, the top five secondary indicators, and relevant tertiary indicators that influence them.

Service Capability (D2) and Operation Management (D3) share the highest weights (0.3317 each), indicating their dominant influence on service efficiency and operational performance (Yang et al., 2022). Infrastructure (D1) ranks third (0.1972), while Social Contribution (D4) is fourth (0.1394), suggesting a comparatively lower but still important role in overall evaluation (Liu, 2021). Among secondary indicators, the top-ranked are Infrastructure Level (E1: 0.1479), Comprehensive Service Quality (E14: 0.1295), Business Efficiency (E13: 0.0916), Warehousing (E3: 0.0758), and Operational Efficiency (E12: 0.0648). These results confirm that physical infrastructure, high-quality service delivery, and operational effectiveness are the primary performance drivers in TLPs (Chen et al., 2021). Infrastructure Level (E1) accounts for 75% of Infrastructure (D1), with Logistics Operation Area (F2: 0.0475) ranking second overall due to its critical role in throughput and efficiency (Liu, 2021).

Under Operation Management (D3), Comprehensive Service Quality (E14: 0.3905) emerges as the most influential sub-factor, underscoring the importance of customer experience and enterprise service performance. At the tertiary level, Customer Satisfaction (F38: 0.0639) ranks highest overall, reinforcing the centrality of user-oriented metrics. Business Efficiency (E13) emphasizes profitability and productivity, with Input-Input-Output Ratio (F36) and Labor Productivity (F37) (both 0.0458) ranking third overall, reflecting the importance of capital and labor efficiency. Warehousing (E3) influences throughput efficiency, with Annual Cargo Throughput (F12) ranked sixth overall, surpassing warehousing area and volume, indicating that handling efficiency outweighs storage capacity in importance. Operational Efficiency (E12: 0.0648) is driven by Logistics Intensity (F34) and Automation Processing Efficiency (F33) but constrained by relatively low Per Capita Workload (F32) and Regional Dispatch Capacity (F35). Sustainability-related indicators such as Social Responsibility (E16) and Ecological Responsibility (E17) (both 0.0558) reflect a growing emphasis on green logistics (Tian et al., 2023). Conversely, lower weights for Equipment Age Coefficient (F18), Green Building Coverage Rate (F50), Public Information Platform Completeness (F27), Number of Environmental Incidents (F44), and PageRank of the Public Information Platform (F26) highlight specific areas requiring further development and strategic improvement.

Overall, the results indicate that infrastructure quality, service excellence, and operational efficiency remain central to TLPs competitiveness, while sustainability and digital modernization are emerging priorities. Under evolving regulatory conditions and rapid technological change, sustainable practices, system upgrades, and digital transformation are likely to become critical for maintaining long-term competitiveness (Tao et al., 2021).

Table 4 Weight for Performance Evaluation Indicator System of TLPs

Primary Indicator	Weight	Secondary Indicator	Local Weight of Secon dary Indica tor	Secon dary Indicator's Overall Weight	Ranking of Secondary Indicator	Tertiary Indicator	Local Weight of Tertiary Indicator	Tertiary Indicator's Overall Weight	Overall Ranking
D1. Infrastructure	0.1972	E1 Infrastructure Level	0.7500	0.1479	1	F1 Actual Land Area of The Park	0.2002	0.0296	10
						F2 Logistics Operation Area	0.3213	0.0475	2
						F3, F4, F5	…	…	…
		E2 Transportation Infrastructure Connectivity	0.2500	0.0493	10	F6, F7, F8, F9	…	…	…

Table 5 (Cont.)

Primary Indicator	Weight	Secondary Indicator	Local Weight of Secondary Indicator	Secondary Indicator's Overall Weight	Ranking of Secondary Indicator	Tertiary Indicator	Local Weight of Tertiary Indicator	Tertiary Indicator's Overall Weight	Overall Ranking
D2. Service Capability	0.3317	E3 Warehousing	0.2286	0.0758	4	F10, F11	…	…	…
						F12 Annual Cargo Throughput	0.5499	0.0417	6
		E4 Transportation	0.1535	0.0509	9	F13, F14, F15, F16	…	…	…
		E5 Loading and Unloading	0.1920	0.0637	6	F17 Number of Handling Equipment	0.1405	0.0089	42
						F18 Equipment Age Coefficient	0.1065	0.0068	48
						F19, F20, F21	…	…	…
		E6 Distribution Processing	0.1349	0.0447	12	F22 Annual Circulation Processing Volume	1.0000	0.0447	5
		E7 Information	0.1180	0.0391	13	F23, F24, 25	…	…	…
						F26 PageRank (PR Value) of the Public Information Platform	0.1065	0.0042	52
						F27 Functionality Completeness of the Public Information Platform	0.1405	0.0055	50
		E8, E9, E10, E11	…	…	…	F28, F29, F30, F31	…	…	…
D3. Operation Management	0.3317	E12 Operational Efficiency	0.1953	0.0648	5	F32 Per Capita Workload	0.1228	0.0080	43
						F33 Automation Processing Efficiency	0.3007	0.0195	18
						F34 Logistics Intensity	0.3843	0.0249	13
						F35 Proportion of Park Dispatch Volume to Regional Transport Volume	0.1922	0.0124	34
		E13 Business Efficiency	0.2761	0.0916	3	F36 Input-Output Ratio	0.5000	0.0458	3
						F37 Labor Productivity	0.5000	0.0458	3
		E14 Comprehensive Service Quality	0.3905	0.1295	2	F38 Customer Satisfaction	0.4934	0.0639	1
						F39, F40	…	…	…
		E15 Safety Management	0.1381	0.0458	11	F41, F42, F43	…	…	…
						F44 Number of Environmental Incidents	0.1194	0.0055	51

Table 6 (Cont.)

Primary Indicator	Weight	Secondary Indicator	Local Weight of Secondary Indicator	Secondary Indicator's Overall Weight	Ranking of Secondary Indicator	Tertiary Indicator	Local Weight of Tertiary Indicator	Tertiary Indicator's Overall Weight	Overall Ranking
D4. Social Contribution	0.1394	E16 Social Responsibility	0.4000	0.0558	7	F45, F46	…	…	…
		E17 Ecological Responsibility	0.4000	0.0558	7	F47, F48, F49	…	…	…
						F50 Green Building Coverage Rate	0.1072	0.0060	49
		E18 Land Intensification	0.2000	0.0279	14	F51, F52	…	…	…

Comparative Summary of SLPs and TLPs Weighting Results

The AHP results show distinct priorities between SLPs and TLPs.

In SLPs, Smart Infrastructure and Intelligent Technology Application (B3) ranks highest (0.3229), led by Smart Logistics Technology Coverage (C10) and Information Technology Investment Ratio (C14). Public Services and Smart Governance (B2) follows (0.2447), with supply chain information system functionalities (C5) as a key driver. Skilled workforce capabilities (C16) also rank highly, reflecting the need for specialized talent to leverage advanced technologies. Although Environmental Sustainability (B5) scores lowest (0.1065), which may be due to its perceived status as an outcome of smart operations rather than a foundational driver, Carbon Emission Reduction Percentage (C18) is the top sustainability metric.

In TLPs, Service Capability (D2) and Operation Management (D3) lead equally (0.3317 each), driven by Comprehensive Service Quality (E14), Customer Satisfaction (F38), and Business Efficiency (E13). Infrastructure (D1) ranks third (0.1972), with Infrastructure Level (E1) and Logistics Operation Area (F2) as key contributors. Sustainability indicators are gaining relevance but remain secondary.

Overall, SLPs prioritize technology, digital infrastructure, and skilled workforce, while TLPs emphasize service quality, operational efficiency, and physical assets. Sustainability is an emerging but secondary focus for both models.

Discussion

The comparative analysis reveals maturity priorities for SLPs and TLPs, shaped by their development orientations and strategic objectives. These priorities stem from fundamentally different evaluation paradigms. Existing industrial park assessments typically focus on environmental performance or location economics, lacking the integrated, maturity-based perspective (Wang et al., 2022). While TLPs frameworks emphasize physical infrastructure, the proposed framework specifically captures the digital transformation enablers; intelligent technology coverage, IT investment, and digital governance, that redefine modern logistics competitiveness.

For SLPs, the dominance of Smart Infrastructure and Intelligent Technology Application (B3) indicates that technological integration, digital infrastructure, and automation are central to maturity advancement. The top rankings of Smart Logistics Technology Coverage (C10) and Information Technology Investment Ratio (C14) confirm that innovation-driven capabilities form the operational backbone of smart parks. This aligns with studies highlighting the role of digital transformation in enhancing efficiency, agility, and competitiveness (Gao et al., 2024; Issaoui et al., 2021). The prominence of Public Services and Smart Governance (B2), particularly supply chain information system functionalities (C5), underscores the importance of interconnected digital platforms for real-time coordination. The high ranking of skilled workforce factors (C16) further affirms that human capital is vital for sustaining technological adoption (Feng & Ye, 2021). Although Environmental Sustainability (B5) has the lowest weight, the leading role of Carbon Emission Reduction Percentage (C18) indicates a growing emphasis on low-carbon development (He et al., 2023). Furthermore, Sub-factors such as "Renewable Energy Equipment Coverage Rate" (C20) received low weights owing to their high upfront costs and long payback periods. These are often deprioritized during initial development phases in favor of foundational technologies that yield faster operational gains (Facchini et al., 2020; Tao et al., 2021).

For TLPs, the highest weights for Service Capability (D2) and Operation Management (D3) demonstrate that service quality, operational efficiency, and customer satisfaction remain the foundation of performance. The influence of Comprehensive Service Quality (E14) and Customer Satisfaction (F38) reflects the continued importance of service excellence. Infrastructure Level (E1) and Logistics Operation Area (F2) confirm the reliance on physical assets and operational capacity (Elhusseiny & Crispim, 2023). Sustainability indicators such as Social Responsibility (E16) and Ecological Responsibility (E17) are gaining relevance but remain secondary, often driven by compliance rather than strategic integration (Liang et al., 2022).

The framework's weights reflect China's rapid digitalization context. In regions characterized by distinct strategic priorities, Europe's Green Deal initiative, for example, environmental factors, such as the utilization of renewable energy (C20), would predictably carry significantly higher weighting (Bibri, 2020). This highlights the model's adaptability: its core dimensions are universally applicable, while their weighting can be calibrated to local conditions. However, the framework's grounding in China's context also presents a limitation. Cross-national applications accounting for governance, cultural, and sustainability variations would strengthen its global relevance (Dzemydienė et al., 2021). Scalability remains a challenge due to inconsistent data collection and measurement standards across regions (Weihua Liu et al., 2022). Modular approaches allowing local customization while retaining a unified core framework may provide a solution (Othman et al., 2022).

Overall, SLPs pursue competitiveness through digital transformation, technology adoption, and workforce development, whereas TLPs rely on service quality, operational management, and infrastructure capacity. Both models show an emerging but secondary emphasis on environmental sustainability, which is expected to grow under regulatory and market pressures.

These findings offer practical guidance for targeted strategies. The study provides practitioners with a clear, actionable hierarchy of strategic priorities, underscoring its operational utility beyond the methodological specifics of AHP. SLPs should continue investing in advanced technologies, integrated platforms, and workforce innovation while accelerating sustainability adoption. TLPs should strengthen digital capabilities and embed sustainability into core operations to facilitate the transition toward smarter, greener logistics. The framework supports strategic decision-making beyond internal assessment, enabling stakeholders to evaluate and compare alternative logistics parks against key priorities for either site selection or partnership decisions. For policymakers, particularly in emerging economies, the results suggest a staged approach to SLPs development. Initial policy support could focus on building foundational digital infrastructure (reflecting the high weight of B3) and fostering public-private partnerships for technology adoption. Subsequently, as parks mature, incentives can be introduced to promote the integration of sustainability metrics (like C18) and workforce upskilling programs (like C16), thereby aligning with the evolving priority structure identified in the framework.

Despite its strengths, the framework has limitations. Rapid technological change requires periodic updates to remain relevant (Tao et al., 2021). Data availability and standardization challenges, particularly in regions with limited digital infrastructure, may hinder implementation (Jović et al., 2022). A methodological limitation stems from the AHP technique itself. Although effective for deriving priority weights from expert input, its dependence on pairwise comparisons may pose cognitive challenges when evaluating numerous criteria. Additionally, the outcomes are influenced by expert panel composition; a factor addressed here through rigorous expert selection but warranting attention in future replications. Although case studies would enhance empirical validation, they were beyond this study's scope. Building directly upon the foundational framework established here, the most immediate and critical next step is to define distinct maturity levels and their specific assessment criteria. This will transform the current diagnostic tool into a fully prescriptive maturity model, providing organizations with a clear evolutionary roadmap. Future work should integrate artificial intelligence, big data analytics, and automated assessment tools to improve adaptability and precision (Sishi & Telukdarie, 2021). Collaboration among academia, industry, and policymakers will be critical for enhancing practical value and addressing technological disparities, especially in parks lacking foundational ICT infrastructure (Hanelt et al., 2021).

Conclusion and Suggestions

A structured maturity assessment framework for SLPs was developed by a multi-stage process integrating a literature review, expert evaluation, and AHP-based weighting. The framework covers economic, governance, technological, human capital, and sustainability dimensions, providing a holistic tool for assessing logistics park maturity. The comparative analysis confirms that SLPs and TLPs follow different development paths, reflecting distinct strategic priorities. SLPs place greater emphasis on Smart Infrastructure and Intelligent Technology Application, as well as Public Services and Smart Governance, whereas TLPs concentrate more on Infrastructure and Service Capability, highlighting the need for digital realignment. The proposed framework offers practical value by supporting evidence-based planning, policy formulation, and digital transformation strategies in the logistics sector. However, the study's scope is limited by the predominantly China-based expert panel and the small sample size, which may affect generalizability. Regional variations in economic development and digital infrastructure were not explored in depth. Future research should expand the geographic scope, conduct cross-regional case studies in areas with distinct developmental contexts, such as Southeast Asia and the European Union, and test the framework's scalability and adaptability in diverse contexts, such as within key nodes of the Belt and Road Initiative or in emerging economies with varying levels of digital infrastructure.

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Author Contributions

Huiqiong Huang: contributed to the study's conceptualization, data collection, analysis and interpretation, and manuscript writing.

Woramol Chaowarat Watanabe: contributed to the development of the methodology and critically reviewed the manuscript.

Conflict of Interests

The authors confirm that there is no conflict of interest to declare for this publication.

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