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A Comparative Analysis of Smart and Traditional Logistics Parks: A Maturity Model Perspective

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Abstract
Smart logistics parks (SLPs) drive economic growth but lack specialised maturity assessment frameworks. This study addresses this gap by developing a maturity assessment framework for SLPs, underscoring distinctions from the traditional logistics parks (TLPs) assessment model to guide the transformation toward smart logistics. The proposed framework comprises five main factors and twenty sub-factors: Smart Economy, Public Services and Smart Governance, Smart Infrastructure and Intelligent Technology Application, Skilled Human Capital, and Environmental Sustainability. These factors were identified through a literature review followed by expert consultations, while the TLPs model is based on China's national standard (2018). The Analytic Hierarchy Process (AHP) was applied to prioritize each factor in both TLPs and SLPs. The results indicate that for SLPs, Smart Infrastructure and Intelligent Technology Application (0.3229) is the most critical factor, followed by Public Services and Smart Governance (0.2447). At the sub-factor level, Smart Logistics Technology Coverage (0.1051) and Percentage of IT Investment (0.0796) are key factors for SLPs. In contrast, TLPs prioritise Service Capability (0.3317) and Operation Management (0.3317), with Customer Satisfaction (0.0639) and Logistics Operation Area (0.0475) as the most influential sub-factors. A comparative analysis reveals that while both models emphasize infrastructure, operational services, and environmental considerations, SLPs focus more on technological innovation and digital governance, whereas TLPs give priority to efficiency and service quality. The framework guides stakeholders, highlighting that SLPs' transformation requires integrating intelligent systems while maintaining efficiency and sustainability. Future research should validate the framework's practical applicability through empirical case studies.

Keywords- Smart logistics parks, Maturity assessment model, Technology-driven supply chains, Digital transformation, Analytic hierarchy process (AHP).

1. Introduction
Smart logistics parks (SLPs) are technologically advanced hubs that utilize digital technologies such as IoT, AI, big data, and automation (Brunetti et al., 2024). Generally, logistics parks provide integrated facilities and services that optimize logistics operations such as warehousing, storage solutions, transportation, and distribution. By applying these technologies, the operations and their efficiency are enhanced. For this reason, SLPs drive economic growth, industrial upgrading, and environmental sustainability, contributing to service innovation and efficiency (Ye et al., 2025). For instance, the Port of Los Angeles handles 9 million TEUs annually, contributing $2.5 trillion to the U.S. economy, while the Port of Rotterdam underpins €500 billion in trade (Port of Los Angeles, 2023; Port of Rotterdam, 2023). Similarly, logistics parks in China have experienced rapid growth in recent years, contributing to reduced operational costs and supporting regional economic development (Fang et al., 2024). Globally, the adoption of SLPs is

accelerating across diverse geographies and sectors. In Europe, Germany's Duisburg Intermodal Terminal strategically employs IoT and AI to improve intermodal rail-waterway logistics efficiency, supporting the EU's broader digital and green logistics strategies (Lim and Limbach, 2023). In Asia, Singapore's Jurong Logistics Hub integrates autonomous vehicles, AI-driven inventory management, and digital twins, aligning with its national Smart Nation Vision (Lopez and Loh, 2023). In the United States, major logistics providers such as Amazon and UPS have implemented robotics, cloud-based platforms, and predictive analytics within their fulfilment centres to optimize operations (Mohammad et al., 2023). Meanwhile, Dubai's Logistics District incorporates blockchain and real-time tracking into regional supply chains under its Vision 2030 framework (Issac, 2024). Even in emerging economies like Brazil and Kenya, governments are piloting digital tools in ports and logistics corridors to improve transparency, reduce congestion, and enhance cross-border trade (Gbahabo et al., 2024). These global examples reflect a converging trend toward intelligent, sustainable, and resilient logistics networks shaped by digital transformation, environmental goals, and strategic policy initiatives (Tran-Dang et al., 2025).

Although traditional logistics parks (TLPs) provide the necessary logistics functions, they remain labour-intensive, relying on physical infrastructure and manual processes (e.g., warehouse management, tracking, and documentation) with limited automation. In contrast, SLPs achieve these functions by applying technologies such as predictive analytics, automated control systems, and real-time route optimization to enhance operational coordination and responsiveness (Chen et al., 2024). Moreover, they place a strong emphasis on sustainability, aiming to minimize environmental footprints, improve the efficiency of resource utilization, and contribute to long-term socio-economic development (Sun et al., 2024). This shift to SLPs is key to building an efficient and adaptive logistics network, ensuring resilience in a digital, sustainability-driven economy (Mutambik, 2024).

Despite the increasing global significance of SLPs, there is still a notable absence of structured frameworks to support their systematic development and evaluation (Pereira et al., 2023). This gap leaves organizations and policymakers uncertain about how to assess the extent of smart transformation and align it effectively with strategic objectives (Mick et al., 2024). To address this challenge, the present study proposes a tailored maturity assessment framework designed specifically for SLPs, aiming to provide both theoretical grounding and practical guidance.

To facilitate the transformation from TLPs to SLPs, it is essential to examine the key characteristics and strategic direction of this transition. The maturity model is a well-established approach for assessing and guiding such developments. The term "maturity" generally refers to the state of being fully developed, advanced, or optimized (Chahidi et al., 2023). The "maturity of SLPs" can be regarded as the goal of their intelligent transformation. This goal means that the logistics park has reached a level of efficiency, integration, and sustainable development in terms of intelligence (Hellweg et al, 2023). Maturity assessments can identify technology gaps, set benchmarks, and guide investments, easing the transition from TLPs. By comparing the maturity model of SLPs with TLPs, stakeholders can better understand logistics evolution and drive competitive transformation. Maturity models are valuable tools for assessing organizational capabilities across various sectors, including manufacturing (Elhusseiny and Crispim, 2023), Industry 4.0 (Chahidi et al., 2023), and logistics and supply chain (Hellweg et al., 2023). By evaluating maturity levels, stakeholders can ensure that the transition process aligns with the intended strategic direction while also determining the extent of transformation required to evolve from TLPs to SLPs.

To conduct a detailed analysis of the maturity assessment model for both TLPs and SLPs, it is important to recognize that TLPs already have established standard characteristics. For instance, the performance evaluation model (PEM) for TLPs, as defined by the National Standardization Administration (2018), provides a structured assessment framework. In contrast, no specific maturity model has been fully developed for SLPs, although several studies have explored related aspects. For example, Tran-Dang et al. (2025) proposed a model integrating logistics, environmental, and production factors through data sharing. Similarly, Pereira et al. (2023) examined broader smart city logistics but did not address the unique requirements of logistics parks. Likewise, Rane et al. (2024) emphasized the role of AI and machine learning in logistics but lacked a dedicated maturity framework for SLPs. These findings indicate a research gap in developing a comprehensive maturity assessment model specifically designed for SLPs.

Therefore, there is a pressing need for a comprehensive maturity assessment model specifically designed to address the unique challenges of SLPs. A comparative analysis with existing models for TLPs would enable a systematic evaluation, drive enhancements in operational efficiency and sustainability, and improve the overall effectiveness of these critical logistics infrastructures. Such a model would provide a strategic roadmap for organizations and stakeholders seeking to transition from TLPs to SLPs, providing clear guidance on necessary improvements and technological advancements.

2. Background

2.1 Intelligent Development Concerns for Smart Logistics Parks

SLPs represent an advanced application of information and communication technology (ICT) within the broader framework of smart cities, either through parallel technological innovations or novel developments (Abouelrous et al., 2023). However, a standardized framework for the construction and operation of SLPs has yet to be established; therefore, drawing upon the developmental experiences of smart cities and smart parks is essential (Lai and Cole, 2023). The key dimensions influencing the intelligent evolution of SLPs are presented in **Table 1**, which summarizes their critical aspects, including dimensions, key elements, descriptions, and supporting literature.

The key dimensions of SLPs include skilled human capital, which emphasizes talent, innovation, community engagement, and smart infrastructure, focusing on ICT, IoT, and data storage. Intelligent information technology enhances operations through cloud computing, big data, and AI, while public services support planning, ecosystem development, and efficiency. Smart governance covers policies, management, and collaboration, and the smart economy prioritizes financial management, profit models, and transport costs. Lastly, environmental sustainability drives green logistics, carbon reduction, renewable energy use, and eco-friendly practices for long-term resilience.

These dimensions encompass both financial and non-financial indicators essential for ensuring the sustainable development of SLPs. Such a holistic approach facilitates the establishment of a robust SLPs ecosystem, driving improvements across key operational areas-including economic efficiency, customer experience, process optimization, and long-term growth (Weerabahu et al., 2023).

These dimensions interact dynamically, forming a self-reinforcing cycle that enhances overall system performance. For example, skilled human capital drives technological advancements, enhancing infrastructure and public services, which in turn improve financial performance. Robust financial performance enables strategic reinvestment in human capital, technological infrastructure, and governance frameworks, thereby establishing a self-perpetuating cycle of organizational improvement (Suresh et al., 2024).

Table 1. SLPs intelligent development in the smart logistics context identified in the literature.

S. No.	Dimensions of concern	Elements	Description	Literature
1.	Skilled human capital	Talents, urban residents' intelligence, creativity, people and community, and innovation ability.	Reflects the state of skilled personnel critical for SLPs.	Mutambik (2024)
2.	Smart infrastructure	Communication infrastructure, intelligent building, basics of IoT perception, communication network foundation, and data storage basics.	Represents the focus on constructing SLPs' infrastructure.	Das (2025)
3.	Intelligent technology application	Network facilities, transportation facilities, the application of cloud computing, big data, IoT, artificial intelligence, RFID technology, etc.	Reflects smart logistics operations within the park.	Hsu et al. (2024)
4.	Public services	Intelligent planning and decision-making, industrial ecological services, and ecological environment, operation state of the settled enterprises.	Reflects the vision and operational state of SLPs.	Treviño-Elizondo et al. (2023)
5.	Smart governance	Policy, governance structure, organizational management, intelligent operation and maintenance, and collaborative ability.	Reflects the management capabilities of SLPs.	Kaiser (2024)
6.	Smart economy	Smart financial management, capital supervision, innovative profit model, net profit, and level of transport cost.	Focuses on financial performance and economic outcomes of SLPs.	Tran-Dang et al. (2025)
7.	Environmental sustainability	Green logistics, carbon footprint reduction, renewable energy utilization, circular economy practices, and eco-friendly transportation solutions.	Emphasizes sustainable practices in SLPs' development and operation.	He et al. (2023)

2.2 Factors Validation and its Application

In this research, the validation of factors for SLPs' maturity assessment is conducted using expert opinions, where the initial selection of factors is based on secondary data. Item-Objective Congruence (IOC) and Content Validity Ratio (CVR) are widely used methods for assessing content validity in research instruments (Rusticus, 2023). IOC measures the alignment between test items and specific objectives by evaluating expert judgments. It typically employs a scale (e.g., -1, 0, +1) to indicate disagreement, neutrality, or agreement on the relevance of each item, with a high IOC index suggesting strong content validity (Agah et al., 2024). CVR quantifies the necessity of individual items, based on expert ratings, and is calculated using a formula that accounts for the proportion of experts who deem an item essential (Rusticus, 2023). A higher CVR score indicates stronger content relevance, with minimum thresholds depending on the number of evaluators (Jeldres et al., 2023).

Research has demonstrated the effectiveness of IOC and CVR in ensuring measurement accuracy. For example, a study on educational assessments applied IOC to refine questionnaire items, ensuring alignment with learning objectives (Agah et al., 2024). Similarly, a medical research study applied CVR to validate survey questions for clinical assessments, confirming their necessity in diagnosing patient conditions (Mary et al., 2025). Prior research demonstrates that IOC and CVR enhance content validity through structured expert assessments, leading to reliable and valid measurement tools.

In our research, IOC and CVR critically refine survey items to ensure alignment with research objectives and expert consensus. IOC evaluates how well each item reflects the intended construct, while CVR helps determine its necessity based on expert consensus. The combined use of IOC and CVR enhances the validity and reliability of our measurement tool, reducing ambiguity and improving the overall quality of data collection (Rusticus, 2023).

2.3 Analytic Hierarchy Process (AHP) and its Application

The analytic hierarchy process (AHP) is a structured decision-making method developed bySaaty in the 1970s (Ashour and Mahdiyar, 2024). It helps decision-makers solve complex problems by breaking them down into a hierarchy of criteria and sub-criteria. Through pairwise comparisons, experts assign relative importance to different factors, which are then converted into weighted scores for objective ranking (Moslem et al., 2023). AHP's strength lies in its ability to integrate qualitative and quantitative data, ensuring a structured and less biased decision-making process (Chaube et al., 2024).

AHP is widely applied in logistics and supply chain management for optimizing supplier selection, warehouse location decisions, transportation mode assessment, and risk analysis (Moslem et al., 2023). For example, it helps evaluate suppliers based on cost, quality, delivery reliability, and sustainability (Galal et al., 2025). In logistics, AHP aids businesses in selecting distribution strategies and facility locations by weighing factors like infrastructure, environmental impact, and operational costs (Tepic et al., 2025). These applications show how AHP supports complex decision-making in supply chains (Moslem et al., 2023).

Beyond logistics, AHP enhances maturity assessment frameworks, particularly for SLPs. Maturity models measure progress using dimensions, criteria, and indicators (Sarker and Klungseth, 2025). AHP improves these models by prioritizing key factors and integrating expert insights with objective data (Moslem et al., 2023). Its pairwise comparisons and consistency checks ensure reliable evaluations, reducing bias (Verma and Rastogi, 2024). In SLPs, AHP helps identify priority areas, assess performance, and guide sustainable growth strategies (Chaube et al., 2024).

3. Methodology

This study follows a structured multi-stage methodology to develop and validate a maturity assessment model for SLPs. The process consists of three key stages: factor identification, importance identification, and result comparison and discussion, as illustrated in **Figure 1**.

3.1 Factor Identification

The first stage begins with the identification of primary maturity factors through a comprehensive review of academic literature, industry white papers, government policy documents, and existing maturity models related to smart cities, industrial parks, and logistics systems. To ensure a broad and relevant scope, a systematic literature review was conducted using databases such as Scopus, Web of Science, and Google Scholar, covering publications from the past 5 years.

To validate and refine the initial set of factors, semi-structured interviews and consultations were conducted with seven experts selected for their expertise in smart logistics, digital infrastructure, logistics park management, and public policy. The panel comprised academic researchers, logistics park operators, a government official involved in digital infrastructure, and representatives from professional logistics associations. A purposive sampling strategy was employed to ensure a balanced representation of perspectives across academia, industry, and government (Aljowder et al., 2023). Each expert independently assessed the relevance of the proposed factors using the IOC index and the CVR method. Factors with IOC scores above 0.5 and CVR values meeting Lawshe's critical thresholds were retained (Rusticus, 2023). For a panel of seven experts, the minimum acceptable CVR value is 0.99, as specified by Lawshe's table (Jeldres et al., 2023).

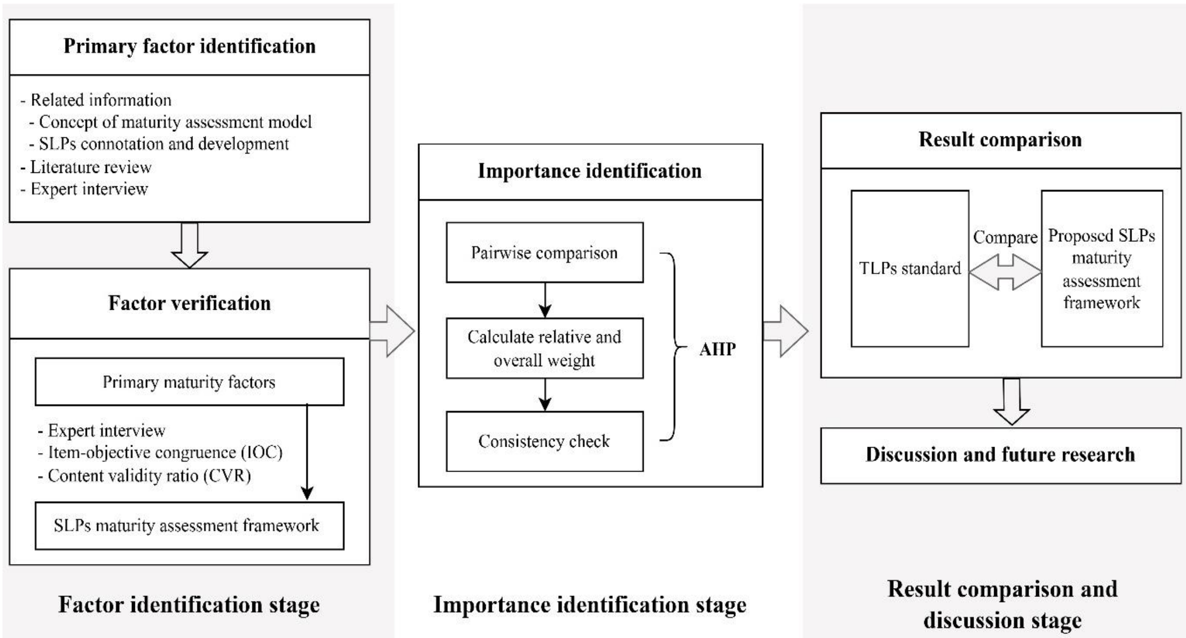

Figure 1. Methodological framework.

3.2 Importance Identification

In the second stage, the AHP was used to determine the relative importance of the identified factors. The same group of seven experts participated in pairwise comparisons using Saaty's scale. These comparisons were used to generate a weight matrix, and the consistency ratio (CR) was calculated for each expert's judgment to ensure reliability ($CR < 0.1$ is considered acceptable) (Tepic et al., 2025). The AHP analysis was performed separately for TLPs and SLPs, allowing for comparative insights into how digital transformation affects factor prioritization.

3.3 Result Comparison and Discussion

The third stage involves a comparative analysis of the resulting maturity models for TLPs and SLPs. Key shifts in priorities are identified. The analysis contextualizes the findings within contemporary industry standards and evolving policy frameworks, delineating a pathway for upgrading TLPs to SLPs.

3.4 Data Collection Considerations

The data collection process involved seven experts who participated in both the validation and weighting stages. While the sample size is small, it aligns with common practices in AHP studies, where expert judgment and depth of insight are prioritized (Verma and Rastogi, 2024). Experts were selected using purposive sampling to ensure representation from academia, industry, and government. This approach aimed to enhance the relevance and comprehensiveness of the input (Chaube et al., 2024). However, the small sample and the fact that all experts were based in China may limit the generalizability of the findings. There is also a risk of selection bias due to shared professional backgrounds among participants (Pant et al., 2024). To reduce this risk, efforts were made to include diverse sectors. Response bias was also minimized by anonymizing individual judgments during data aggregation (Bike and Ruichang, 2023).

4. Maturity Assessment Framework of Smart Logistics Parks

4.1 Smart Logistics Parks Maturity Assessment Factors Framework

The framework was developed through expert input and systematic screenings to ensure factor relevance, practicality, and adaptability. Redundant indicators were removed, and only high-validity factors were retained. The identified factors, presented in **Figure 2** and **Table 2**, include smart economy, public services and smart governance, smart infrastructure and intelligent technology application, skilled human capital, and environmental sustainability. **Figure 2** illustrates the overall framework, while **Table 2** provides a detailed breakdown of each factor and its corresponding sub-factors.

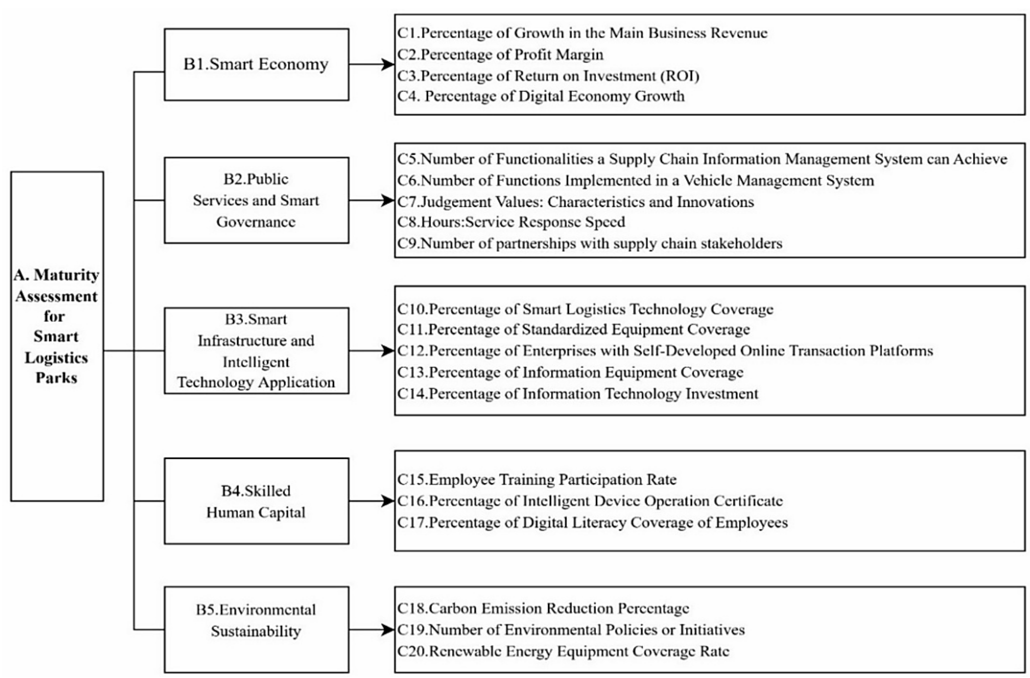

Figure 2. Framework for maturity assessment of the SLPs.

The Smart Economy (B1) is a fundamental factor in SLPs, encompassing all economic considerations related to smart operations and their impact on overall economic performance. It is prioritized due to its direct influence on organizational outcomes, with most logistics parks emphasizing economic efficiency and sustainability (Alzate et al., 2024). Public Services and Smart Governance (B2) is pivotal in enhancing the efficiency of service delivery and regulatory oversight through the integration of digital technologies. This factor not only promotes industrial synergy among logistics parks but also contributes to higher stakeholder satisfaction and the development of a well-regulated, efficient, and sustainable logistics ecosystem (Pereira et al., 2023).

Smart Infrastructure and Intelligent Technology Application (B3) constitutes the operational backbone of SLPs, directly supporting internal processes. The implementation of advanced technologies and resilient infrastructure is fundamental to driving digital transformation, thereby making this domain a key component of the maturity evaluation framework (Kocaoglu, 2024). Moreover, Skilled Human Capital (B4) emphasizes the importance of workforce adaptability, continuous innovation, and structured training systems. A capable and agile workforce is essential to effectively support and sustain the transition toward smart logistics operations (Viet and Quoc, 2023). Finally, Environmental Sustainability (B5) addresses the adoption of eco-friendly practices and long-term sustainability strategies to minimize environmental impact while maintaining operational efficiency (Brunetti et al., 2024). Through a step-by-step validation process, the framework ensures a scientific and reliable approach, confirming the key aspects that should be prioritized in SLPs' development. The proposed framework comprehensively integrates all critical dimensions essential for evaluating SLPs' characteristics.

Table 2. 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 (Rojas-García et al., 2024).
	C2. Percentage of Profit Margin	Reflects the park's cost control and performance in logistics, warehousing, supply chain management, digitalization, and intelligent services (Rojas-García et al., 2024).
B1. Smart Economy	C3. Percentage of Return on Investment (ROI)	Measures the returns generated from investments in intelligent facilities, technologies, and logistics services (Lee et al., 2023).
	C4. Percentage of Digital Economy Growth	Indicates the growth of the digital economy in areas such as information technology, big data, and artificial intelligence (Chen, 2023).
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 (Kocaoglu, 2024).
	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 (Aljowder et al., 2023).
	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 (Wang et al., 2025).
	C9. Number of partnerships with supply chain stakeholders	Indicates the level of ecosystem collaboration and value chain integration (Przybylska 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 applications in the park, expressed as the ratio of operations using intelligent technology to total logistics operations (Kocaoglu, 2024).
	C11.Percentage of Standardized Equipment Coverage	The number of enterprises in the park that use standardized logistics equipment (Kocaoglu, 2024).
	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 (Kocaoglu, 2024).
	C13.Percentage of Information Equipment Coverage	The proportion of deployed information devices in the park relative to its overall needs (Lai and Cole, 2023).
	C14.Percentage of Information Technology Investment	The park’s capital expenditure is directed primarily towards IT infrastructure, digital systems, and intelligent equipment to underpin its digital transformation agenda (Lai and Cole, 2023).
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 (Viet and Quoc, 2023).
	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 (Weerabahu et al., 2023).
	C17.Percentage of Digital Literacy Coverage of Employees	The proportion of employees in a logistics park with specific digital skills and knowledge (Zhao et al., 2024a).
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 (He 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 within the park utilizing renewable energy equipment serves as an indicator of their commitment to adopting green energy solutions (Tian et al., 2023).

4.2 Determining Factor Importance for the Maturity Assessment of Two Models

To evaluate the relative significance of each factor in both SLPs and TLPs, the AHP was applied to each model separately, enabling a comparative analysis of factor prioritization from different perspectives. This section presents the results for SLPs and TLPs independently, while the comparative analysis and key findings are discussed in the discussion section.

(1) Smart logistics parks maturity assessment model

Table 3 presents the weight distribution of factors in the SLPs maturity assessment framework using the AHP. Among the five main factors, Smart Infrastructure and Intelligent Technology Application (B3) holds the highest weight (0.3229), indicating its critical role in SLPs' development. Within this factor, the Smart Logistics Technology Coverage Rate (C10) has the highest overall weight (0.1051, ranked 1st), followed by the Information Technology Investment Ratio (C14) (0.0796, ranked 2nd). These findings underscore the central role of technological innovation and digital infrastructure in the maturity of SLPs (Wang et al., 2025). Public Services and Smart Governance (B2) ranks second (0.2447), with the Number of Functionalities a Supply Chain Information Management System Can Achieve (C5) receiving the highest sub-factor weight (0.0706, ranked 3rd), emphasizing its role in digital transformation and supply chain optimization (Kaiser, 2024). The Intelligent Equipment Operation Certification (C16) under the Skilled Human Capital (B4) carries substantial weight (0.0693, ranked 4th), reflecting the critical demand for technically proficient personnel in smart logistics operations (Viet and Quoc, 2023).

Within Smart Economy (B1), the Percentage of Growth in Main Business Revenue (C1) holds the highest weight (0.0632, ranked 5th), signifying its direct impact on financial performance. In contrast, the Percentage of Return on Investment (C3) has the lowest weight (0.0316), indicating its relatively indirect contribution compared to direct economic benefits and sustainability drivers (Lee et al., 2023). In the Public Services and Smart Governance (B2), Supply Chain Information System Functionalities (C5:0.2886) demonstrate significantly greater importance than Partnerships with Supply Chain Stakeholders (C9:0.1256). This weighting distribution suggests that digital infrastructure capabilities exert a more substantial influence on SLPs' performance than external partnership networks (Das, 2025). Smart Infrastructure and Intelligent Technology Application (B3) reveal a distinct prioritization pattern. Core technological drivers - particularly Smart Logistics Technology Coverage (C10) and IT Investment Ratio (C14) - emerge as primary determinants of SLPs' intelligence. In contrast, implementation factors like Standardized Equipment Coverage (C11) and Enterprise Self-Developed Platforms (C12) play secondary, supportive roles in the technological ecosystem (Kocaoglu, 2024). In Skilled Human Capital (B4), the high weight of Intelligent Device Operation Certification (C16) reflects the critical role of technical skills in automation and intelligent operations, whereas Digital Literacy Coverage (C17) remains foundational but holds the lowest weight (Liu and Ye, 2023).

Although Environmental Sustainability (B5) holds the lowest weight among the primary dimensions (0.1065), its sub-factor Carbon Emission Reduction Percentage (C18: 0.4934) ranks as the most influential indicator within this category, emphasizing its central role in shaping environmental performance. In contrast, Renewable Energy Equipment Coverage (C20: 0.1958) has the lowest weight, as its impact is more indirect compared to emission reduction and policy implementation (Tian et al., 2023). The top five overall 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 park's core operational and technological priorities (Gao et al., 2024; Hsu et al., 2024). Conversely, the lowest-ranked sub-factors are 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), which currently hold lower priority but may gain significance as technological advancements progress and environmental policies evolve (Hsu et al., 2024; Zhao et al., 2024a). These findings highlight the central role of technological integration, digital infrastructure, and workforce development in the maturity of SLPs while suggesting that sustainability—though presently assigned a lower priority—is likely to gain greater importance in the future.

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 Digital3 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 4 primary indicators, 18 secondary indicators, and 52 tertiary indicators. **Table 4** presents the PEM and corresponding factor weights for TLPs. In this context, **Table 4** selectively displays some indicators, including primary indicators, the top five ranked secondary indicators, and relevant tertiary indicators that influence them.

Service Capability (D2) and Operation Management (D3) share the highest weights (0.3317 each), reflecting their pivotal influence on service efficiency and operational performance. Infrastructure (D1) ranks third (0.1972), while Social Contribution (D4) ranks fourth (0.1394), indicating its lower but still essential role in logistics park evaluation. Among secondary indicators, the highest-ranked include 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). The findings suggest that infrastructure development, high-quality service delivery, and effective operations are key determinants of performance in TLPs (Lo Storto and Evangelista, 2023). Notably, Infrastructure Level (E1) accounts for 75% of Infrastructure (D1), emphasizing the significance of physical assets, with Logistics Operation Area (F2: 0.0475) ranking second overall due to its critical impact on throughput and efficiency.

Table 4. Weight for performance evaluation indicator system of TLPs.

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
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	…	…	…
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
D2. Service Capability	0.3317	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

Table 4 continued…

		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
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	…	…	…

Comprehensive Service Quality (E14: 0.3905), the most influential indicator under Operation Management (D3), underscores the critical role of customer experience and enterprise service quality. Among the tertiary indicators, Customer Satisfaction (F38: 0.0639) ranks highest, further emphasizing the centrality of user-oriented performance metrics. Business Efficiency (E13) prioritizes profitability and productivity, with Input-Output Ratio (F36) and Labor Productivity (F37), each weighted at 0.0458, ranking third overall and demonstrating their importance in capital and labour efficiency. Warehousing (E3) impacts throughput efficiency, with Annual Cargo Throughput (F12, ranked 6th overall) being the most critical indicator, surpassing warehousing area and volume, emphasizing the importance of handling efficiency over storage capacity. Operational Efficiency (E12: 0.0648) is driven by Logistics Intensity (F34) and Automation Processing Efficiency (F33) but is constrained by low Per Capita Workload (F32) and Regional Dispatch Capacity (F35). Sustainability factors, including Social Responsibility (E16) and Ecological Responsibility (E17), each at 0.0558, indicate an increasing focus on green logistics (Tian et al., 2023). However, Equipment Age Coefficient (F18), Green Building Coverage Rate (F50), Public Information Platform Completeness (F27), Number of Environmental Incidents (F44), and PageRank (PR value) of the Public Information Platform (F26) rank lower, signalling areas for improvement. Under dynamic regulatory shifts and continuous technological innovation, sustainable operational practices, system modernization, and digital transformation emerge as key determinants of sustained competitive advantage in logistics systems (Ye et al., 2025).

5. Discussion

5.1 Comparative Analysis of the two Frameworks

The SLPs' maturity assessment framework (proposed framework) is compared with the TLPs performance evaluation model (PEM) to examine their distinct characteristics and effectiveness. A comparative analysis of the weighting results aims to address key questions, including whether the factors in both models are identical, whether their assigned weights differ, and how priority shifts between SLPs and TLPs influence logistics development. The results of this comparison are presented in **Table 5** and **Table 6**.

Table 5. Comparison between the top 5 rank for both SLPs and TLPs.

Category	SLPs	Weight	Analysis	TLPs	Weight	Analysis
Technology & Digitalization	Smart Logistics Technology Coverage (C10)	0.1051	SLPs prioritize advanced logistics technologies to enhance automation and operational efficiency.	Customer Satisfaction (F38)	0.0639	TLPs focus more on customer experience, as service quality directly impacts market competitiveness.
Information Systems & Smart Management	IT Investment (C14)	0.0796	High IT investment enhances data-driven operations and supply chain collaboration.	Logistics Operation Area (F2)	0.0475	Physical space remains critical in TLPs, as it reflects capacity and throughput efficiency.
Supply Chain Management	Number of Functionalities a Supply Chain Information Management System can Achieve (C5)	0.0706	Emphasizes real-time visibility and efficient logistics coordination.	Input-Output Ratio (F36)	0.0458	TLPs prioritize financial efficiency, measuring capital utilization effectiveness.
Automation & Equipment	Smart Equipment Operation Certification (C16)	0.0693	Reflects the importance of compliance and reliability in intelligent logistics operations.	Labor Productivity (F37)	0.0458	TLPs rely more on human labour, making workforce efficiency a key performance indicator.
Economic Growth	Main Business Revenue Growth (C1)	0.0632	Highlights SLPs focus on industrial expansion and business model innovation.	Annual Processing Volume (F22)	0.0447	Processing capacity is crucial for TLPs, influencing logistics throughput and operational scale.

Table 5 provides a comparative evaluation of the five highest-ranked factors between SLPs and TLPs, revealing statistically significant divergences in strategic priorities that drive contrasting logistics development trajectories. SLPs prioritize technology and digitalization, with Smart Logistics Technology Coverage (C10: 0.1051) being the highest-ranked factor, emphasizing automation and operational efficiency. This priority accelerates the transition toward intelligent logistics systems, enabling real-time data integration and predictive analytics. In contrast, TLPs place greater importance on service quality, with Customer Satisfaction (F38: 0.0639) ranking highest, reflecting its direct impact on market competitiveness in traditional logistics operations. The 64% higher weight for technology in SLPs, compared to service in TLPs, underscores a shift from labor-intensive processes to technology-driven efficiency gains (Hsu et al., 2024; Sarker and Klungseth, 2025).

In information systems and smart management, IT Investment (C14: 0.0796) constitutes a pivotal enabler for SLPs, facilitating data-integrated operations and supply chain synchronization. This emphasis supports the development of connected logistics ecosystems, where seamless data flow enhances end-to-end visibility. TLPs, conversely, emphasize physical logistics space, where Logistics Operation Area (F2: 0.0475) directly correlates with capacity and throughput efficiency. The 67% higher weight of IT investment in SLPs (vs. physical space in TLPs) highlights how digital infrastructure is overtaking physical expansion as the primary driver of logistics growth, a trend consistent with global smart logistics market forecasts (Elhusseiny and Crispim, 2023).

In supply chain management, SLPs emphasize real-time logistics coordination via Supply Chain Information System Functions (C5: 0.0706), while TLPs focus on financial efficiency through Input-Output

Ratio (F36: 0.0458). This divergence demonstrates that SLPs prioritize supply chain agility to adapt to volatile markets, whereas TLPs optimize for cost efficiency in stable environments. The 54% higher weight on supply chain intelligence in SLPs underscores the rising importance of dynamic routing and demand forecasting in modern logistics (Pereira et al., 2023).

In automation & equipment, SLPs prioritize smart equipment certification (C16: 0.0693) to ensure compliance and reliability, whereas TLPs rely more on human labour, with Labor Productivity (F37: 0.0458) as a key indicator of workforce efficiency. Lastly, in economic growth, SLPs focus on industrial expansion and business model innovation, as seen in Main Business Revenue Growth (C1: 0.0632), whereas TLPs emphasize processing capacity, with Annual Processing Volume (F22: 0.0447) influencing throughput and operational scale.

These contrasts reflect a deeper strategic divergence: SLPs emphasize digital transformation, data intelligence, and system-level automation, while TLPs remain grounded in physical infrastructure, service reliability, and cost efficiency (Pereira et al., 2023). The weighting differences—specifically the 2.1x higher aggregate weight of digital factors in SLPs (0.3229 for smart infrastructure vs. 0.1972 for physical infrastructure in TLPs)—quantify how SLPs are reshaping logistics from a transactional service to an innovation-driven ecosystem. This shift facilitates faster and more adaptive responses to supply chain disruptions, as evidenced by case studies on smart logistics adoption (Sarker and Klungseth, 2025).

For instance, the prominence of IT Investment and Smart Logistics Technology Coverage in SLPs (C10, C14) implies a shift toward predictive analytics, automated coordination, and platform-based logistics services. Such technological prioritization enables the deployment of IoT sensors and AI algorithms, fostering greater operational efficiency and advancing sustainability objectives in logistics operations (Rane et al., 2024). Conversely, TLPs' prioritization of customer satisfaction and operational throughput (F38, F2) reveals a model still reliant on labour productivity and physical infrastructure.

Table 6 provides a comprehensive comparison of the SLPs' maturity assessment framework and the TLPs' performance evaluation model, revealing fundamental shifts in logistics park priorities. While SLPs adopt a three-layer structure (1/5/20) focusing on digital transformation and smart maturity, TLPs implement an expanded four-layer architecture (1/4/18/52), prioritizing conventional logistics efficiency. Both models share key dimensions, including infrastructure, operations, services, environment, and social contributions, yet SLPs uniquely incorporate smart economy and skilled human capital, reflecting their reliance on technology-driven logistics. The weighting results indicate a shift in development priorities between SLPs and TLPs. SLPs assign greater importance to Smart Infrastructure and Intelligent Technology Application (B3: 0.3229) and Public Services and Smart Governance (B2: 0.2447), underscoring the growing role of automation and digital systems. In contrast, TLPs place their emphasis on Service Capability (D2: 0.3317) and Operation Management (D3:0.3317), reflecting a continued reliance on traditional logistics performance metrics. This divergence not only reveals differing evaluation frameworks but also points to a deeper strategic transformation. The elevated weights attributed to digital infrastructure and smart governance by SLPs suggest a progressive orientation toward agility, system integration, and innovation (Li et al., 2023). TLPs, by contrast, remain grounded in a model centered on physical efficiency and stable operational execution, indicative of a more static development trajectory (Elhusseiny and Crispim, 2023).

Furthermore, SLPs demonstrate a pronounced focus on digital infrastructure and smart services, whereas TLPs continue to prioritize service functionality and operational processes. The strategic implications of this shift are significant. Notably, SLPs allocate considerable weight to Skilled Human Capital (B4: 0.1405)—a dimension absent from the TLPs model. This highlights the recognition within SLPs of workforce adaptability and digital competencies as pivotal to successful transformation (Soni, 2023). In contrast, the exclusion of human capital considerations in TLPs reflects a lag in acknowledging the role of skilled labor in facilitating digital transitions. Additionally, the greater emphasis placed on smart infrastructure within SLPs underscores the growing importance of cloud computing, IoT platforms, and automated systems. These technologies are redefining logistics park operations by enabling real-time decision-making, cross-organizational collaboration, and responsive adaptation to disruptions (Tran-Dang et al., 2025).

Table 6. Structural and weighting comparisons of the two frameworks.

Questions	Issues	SLPs	TLPs	Analysis
Are the factors of the two frameworks the same?	(1). Structural Comparison	Factor framework: 3 layers Goal: SLPs' maturity assessment. Structure:1/5/20	Factor framework: 4 layers Goal: logistics park performance evaluation. Structure:1/4/18/52	The dimensions and factors of logistics parks exceed those of SLPs, as the former is the foundation with general traits, while the latter focuses on "smart."
	(2). Similar Factors	B2, B3, B5	D1, D2, D3, D4	Both regard infrastructure, operations, services, environment, and society as key factors.
	(3). Unique Factors	B1, B4, all the sub-factors	All the secondary and tertiary indicators	The two differ in specific indicators: the SLPs focus on smart technology, while the TLPs emphasize traditional logistics operations and services.
Is the importance of the factors the same?	I. Focus Areas and Priorities	B3>B2>B1>B4>B5 Top5: C10, C14, C5, C16, C1	D2>D3>D4>D1 Top5: F38, F2, F36, F37, F22	SLPs: Prioritize infrastructure, technology, operations, and service delivery, with smart logistics technologies and IT investment as key drivers. TLPs: Emphasize service quality, operational efficiency, and capacity, with increasing focus on social contribution.
	II. Comparison of Weight Distribution			
	(1) Infrastructure	0.3229 (B3 Smart Infrastructure and Intelligent Technology Application)	0.1972 (D1 Infrastructure)	SLPs prioritize smart technology and digital infrastructure, while TLPs focus on physical infrastructure.
	(2) Service and Management	0.2447 (B2 Public Services and Smart Governance)	0.3317 (D2 Service Capability)	SLPs emphasize integrating smart technologies into service functions, with partnerships across the supply chain as a key differentiator. TLPs focus on core logistics tasks such as storage, transport, handling, and information services.
	(3) Economic Performance	0.1854 (B1 Smart Economy)	Indirectly reflected in service capabilities, such as revenue from financial and value-added services.	SLPs emphasize economic factors such as ROI, revenue growth, and profit margin, reflecting the tangible benefits of smart technology adoption. In contrast, TLPs prioritize operational economic outputs, focusing on efficiency and throughput.
	(4) Social and Environmental	0.1065 (B5 Environmental Sustainability)	0.1394 (D4 Social Contribution)	Both assign low weight to social and environmental factors but differ in emphasis: SLPs focus on sustainability through carbon reduction and new energy adoption, while TLPs balance social and ecological responsibilities.
	(5) Skilled Human Capital	0.1405 (B4 Skilled Human Capital)	Not mentioned	SLPs emphasize the foundational role of smart human capital, while TLPs focus on performance evaluation, not mentioning human capital.
	(6) Operations Management	Not listed separately	0.3317 (D3 Operation Management)	TLP's performance focuses on efficiency, automation, and customer satisfaction, which is reflected through smart governance and technology applications.

The economic evaluation further illustrates this divergence: SLPs assess financial performance through direct factors such as ROI and revenue growth, whereas TLPs rely on indirect measures, focusing on service capacity as a proxy for economic output. Both models assign relatively low weight to social and environmental concerns, yet SLPs adopt a more proactive sustainability strategy—targeting initiatives such as carbon reduction and renewable energy—while TLPs adhere to a more balanced, compliance-oriented approach (Chen, 2023; Sun et al., 2024). These efforts align with global climate goals and are essential for reducing environmental impact across logistics networks (He et al., 2023). Notably, SLPs emphasize Skilled Human Capital (B4: 0.1405), recognizing workforce adaptability as a key driver of smart logistics, whereas TLPs do not explicitly consider human capital as a factor. These differences in weighting reflect a clear maturity progression—from service-oriented TLPs to innovation-driven SLPs. This shift demands a fundamental rethinking of infrastructure, workforce skills, and service design, signalling a profound transformation in how value is generated within logistics ecosystems (Li et al., 2023). The contrast underscores the significant technological advancement required to move from TLPs to SLPs, highlighting the urgent need for digital transformation and strategic workforce development in the evolving logistics landscape (Kumar et al., 2024).

Both frameworks integrate infrastructure, socio-environmental, and economic dimensions within a hierarchical structure that decomposes key components into measurable sub-levels. Despite their shared goal of comprehensive performance evaluation, they diverge in focus, reflecting differing strategic priorities. As shown in **Table 7**, each framework presents distinct strengths and limitations that influence logistics development pathways. The SLPs framework's forward-looking emphasis on technological innovation (0.3229 weight on smart infrastructure) drives the sector toward Industry 4.0 integration, enabling capabilities like autonomous warehousing and blockchain-based supply chain tracking. This focus aligns with global logistics trends, as smart technology adoption is projected to increase operational efficiency by an average of 15% per year through 2025 (Gao et al., 2024). Conversely, the TLPs model's operational orientation (0.3317 combined weight on service and operation management) sustains traditional logistics functions but may limit agility in dynamic markets. The 1.7x higher weight on digital factors in SLPs (vs. traditional metrics in TLPs) indicates that logistics development is increasingly determined by technological maturity rather than physical capacity, a paradigm shift with implications for workforce skills and infrastructure investment priorities (Kumar et al., 2024).

Table 7. Strengths and weaknesses of the two frameworks.

Framework	Strengths	Weaknesses
SLPs	Future-Oriented: Emphasizes smart technology and infrastructure, aligning with the digital transformation of logistics. Environmental Responsibility: Incorporates sustainability factors such as carbon emissions reduction and renewable energy adoption.	Overemphasis on Technology: May overlook traditional logistical challenges such as transportation and warehousing efficiency.
TLPs	Balanced Approach: Integrates infrastructure, service, operations, and social contributions into a comprehensive evaluation model. Detailed Metrics: Includes 52 tertiary indicators, providing a granular and actionable assessment of logistics park performance.	Limited Focus on Technology: Places less emphasis on smart technology and digital innovation compared to the SLPs framework.

5.2 Implications and Limitations

This framework presents a structured, evidence-driven approach to evaluating SLPs' maturity, addressing a critical research gap in quantitative assessment. Distinct from TLPs models, it incorporates hierarchical architectures and quantitative metrics across five core dimensions—economy, governance, technology, human capital, and sustainability—to capture SLPs-specific characteristics. The use of AHP for weight assignment enables a transparent and rational prioritization process, supporting more effective strategic planning, resource deployment, and performance comparison across the industry. In addition, this study demonstrates how the proposed framework advances beyond TLPs models by placing greater emphasis on technological integration and sustainability—two pillars increasingly central to global logistics development (Li et al., 2023). The framework's scalability enables cross-regional and cross-ecosystem adaptation, positioning it as a dual-purpose tool for academic research and industry applications. Socioeconomic and technological disparities profoundly influence SLPs' maturity trajectories. Economically advanced regions tend to adopt frontier technologies (e.g., AI, IoT), whereas less-developed areas prioritize basic digital infrastructure deployment. Tailoring the framework to account for contextual factors—such as policy environments, digital maturity, and industrial composition—can improve its relevance and utility across different regional settings (Liu et al., 2024).

Maturity factor weights vary with regional economic and technological contexts. In high-income economies, Smart Infrastructure and Intelligent Technology Application (B3) may be weighted more heavily, while in developing regions, Public Services and Smart Governance (B2) and basic infrastructure often dominate. Jurisdictions with carbon pricing or renewable energy mandates typically assign greater weight to Environmental Sustainability (B5) (Teerasoponpong et al., 2025). Overall weight patterns indicate a strategic transition from capacity- and cost-driven operations toward technology leadership and environmental stewardship. Higher shares for digital and sustainability factors suggest that competitive advantage now depends more on innovation and resilience than on physical scale (Mutambik, 2024). SLPs can apply specific carbon reduction measures such as AI-based route optimization, fleet electrification, and waste heat recovery. Renewable energy integration may include on-site solar generation, wind–solar hybrids with storage, and smart grid connections. Such measures can reduce logistics carbon intensity by up to one-third while enhancing operational resilience (Huang and Mao, 2024).

The framework has practical implications for key stakeholders. For policymakers, it offers a tool to guide infrastructure investment, digital innovation policy, and sustainable development targets with a focus on carbon footprint reduction and renewable energy integration. For logistics operators and developers, the framework offers strategic guidance on advancing digital transformation, enhancing workforce capabilities, and improving operational efficiency. Furthermore, it supports investors and supply chain partners in assessing park readiness and future growth potential.

Notwithstanding its merits, the framework harbours limitations requiring further inquiry. Regulatory inconsistencies—such as divergent data privacy policies, fragmented cross-border logistics regulations, and uneven enforcement mechanisms—pose challenges to interoperability and hinder adoption (Bandaranayake et al., 2024; Shandilya et al., 2024). Moreover, region-specific governance gaps and the absence of unified digital standards further complicate implementation, particularly in transnational supply chains. Infrastructure investment gaps in developing regions—manifested as insufficient funding for basic ICT—exacerbate data scarcity and stymie digital transformation (Liu and Zhao, 2024). These infrastructural deficits often interact with regulatory barriers, amplifying complexity in areas where institutional capacity is limited. Sustainability initiatives in SLPs, such as solar-powered warehousing or electric vehicle fleets, are often constrained by unequal access to renewable energy infrastructure, which varies significantly across regions. Ongoing technological progress requires that the framework be regularly updated to remain aligned with evolving industry standards and practices (Ferraro et al., 2023). Data availability and standardization challenges—especially in regions with limited digital infrastructure—may hinder implementation (Kocaoglu, 2024). Although incorporating practical case studies would enhance the framework and support empirical validation, this lies beyond the current study's scope and will be pursued in future research. While the framework provides a comprehensive maturity assessment, future studies should prioritize integrating AI, big data analytics, and automated assessment models to enhance adaptability and precision (Rane et al., 2024). Additionally, interdisciplinary collaboration among academia, industry, and policymakers is critical to refining the framework's practical utility and aligning it with the dynamic smart logistics landscape. Technological disparities also intersect with sustainability gaps: many SLPs lack energy-efficient technologies, such as smart grid systems or carbon emission tracking tools, which are essential for implementing effective carbon reduction strategies. These challenges highlight the importance of phased implementation strategies, the establishment of region-specific data collection standards, and targeted investments in green logistics infrastructure (Liu and Zhao, 2024). Although the model is grounded in China's national standards, its core design is adaptable across international contexts. Expanding the framework through cross-national comparisons and regional adaptations—taking into account variations in governance structures, cultural norms, and sustainability agendas, including carbon pricing policies and renewable energy targets—would significantly enhance global applicability (Zhao et al., 2024b).

Scalability challenges persist primarily due to non-harmonized regional data collection mechanisms (Liu and Zhao, 2024). Inconsistent definitions of logistics performance and measurement standards across jurisdictions further complicate benchmarking endeavours. Future iterations should also integrate sustainability metrics, such as carbon intensity per unit of logistics output or renewable energy share in park operations, to address the growing demand for environmental accountability. Iterations of the model should explore modular approaches that allow local customization while retaining a core assessment structure (Ferraro et al., 2023).

5.3 Transition Challenges

The transformation from TLPs to SLPs presents several barriers. First, the deployment of smart technologies demands substantial infrastructure investment, particularly when it involves retrofitting existing legacy systems (Plekhanov et al., 2023). Second, low levels of technological literacy among logistics operators may hinder the adoption of new platforms and tools (Viet and Quoc, 2023). Third, regulatory constraints and inconsistent policy enforcement may limit innovation or delay digital implementation (Liu et al., 2024). Addressing these challenges calls for comprehensive policy support, workforce training initiatives, and financial incentives to ease the transition (Qiao et al., 2024).

6. Conclusion

This study developed a structured maturity assessment framework for SLPs, addressing the critical gap in evaluating their digital transformation and operational evolution. By assigning AHP-weighted factors and contrasting them with TLPs, the framework reveals fundamental shifts in logistics priorities.

Key contributions include identifying technology-driven transformation: SLPs prioritize Smart Infrastructure and Intelligent Technology Application (0.3229), Public Services and Smart Governance (0.2447), while TLPs focus on Infrastructure (0.1972) and Service Capability (0.3317), necessitating digital realignment. The study also highlights SLPs' integration of Environmental Sustainability (0.1065) and Skilled Human Capital (0.1405)—areas where TLPs lag—along with a quantitative framework to benchmark maturity and guide investments in automation, renewable energy, and upskilling.

The study's practical implications include policymakers can use the framework to incentivize digital adoption (e.g., IoT subsidies) and standardize sustainability metrics; logistics operators can leverage AHP-weighted factors (e.g., smart tech coverage, ROI) to identify gaps for TLPs-to-SLPs upgrades; and researchers can expand the model to include dynamic capabilities (e.g., supply chain resilience) and regional adaptations for emerging economies.

Limitations and future work for the study include its China-centric expert panel, warranting global validation for cross-cultural applicability; the need to periodically update the framework due to rapid AI and blockchain advancements; and the requirement for empirical validation through case studies of SLPs implementing the framework to test its real-world efficacy.

Conflict of Interest

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

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During the preparation of this work the author(s) used generative AI in order to improve the language of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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