

A structured maturity model for evaluating smart logistics parks transformation: Case study in western China

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Abstract

The transformation of traditional into smart logistics parks (SLPs) requires a structured framework for assessing maturity and guiding development. Existing maturity models, often adapted from smart city or industrial park frameworks, lack specificity and empirical validation for the logistics park context. To address this gap, this study constructs and validates a data-driven maturity model for SLPs by integrating a literature review, expert consultation, and case studies of two logistics parks in western China. The model comprises five dimensions—Smart Economy, Public Services and Smart Governance, Infrastructure and Intelligent Technology Application, Skilled Human Capital, and Environmental Sustainability—and defines 20 measurable factors. These factors are evaluated through a four-level maturity framework progressing from Initial to Optimization stages, corresponding to the conventional levels of Initial, Defined, Managed, and Leading. The application revealed that both parks were positioned between the Initial and Growth stages. Logistics Park 2 excelled in digital infrastructure and technology adoption, as well as workforce digital literacy, whereas Logistics Park 1 enjoyed advantages in operational ROI and stakeholder integration. While for both parks, Public Services and Smart Governance reached the Growth stage, Smart Economy and Environmental Sustainability lagged, reflecting reliance on volume-based growth and underdeveloped sustainability outcomes. The model differentiated between transitional and emerging SLPs, proving its value as a diagnostic and strategic tool. One limitation, however, is the model's initial validation within the two case studies in western China, and future research should expand the application to diverse contexts to enhance generalizability and robustness.

Keywords: Smart logistics park, Maturity model, Data-driven assessment, Digital transformation, Case study

1. Introduction

The transformation of traditional logistics parks into smart logistics parks (SLPs) is driven by the rapid integration of advanced digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and big data analytics. These technologies fundamentally reshape logistics operations by enabling automation, data-driven decision-making, and real-time coordination across supply chains [1]. Unlike traditional facilities that focus primarily on warehousing, transportation, and distribution, SLPs are technologically advanced hubs supported by integrated digital infrastructure, and their primary objective is to enhance operational efficiency, connectivity, and sustainability [2]. This transformation aligns with the concept of “Logistics Park 4.0,” which applies Industry 4.0 principles through the incorporation of cyber-physical systems, platform-based collaboration, and intelligent service ecosystems [3]. Within the broader trend of global supply chain digitalization, SLPs are increasingly recognized as critical nodes in emerging smart logistics ecosystems [4].

Despite the growing attention to policy and technological investment, the pace and depth of smart transformation vary significantly across regions and individual parks. This heterogeneity underscores the need to evaluate not only technology adoption but also the institutional, organizational, and human dimensions that determine transformation readiness and sustainability [5].

The practical impacts of the development of SLPs are evident across multiple international contexts, demonstrating tangible improvements in operational efficiency, cost reduction, and sustainability performance. In Europe, Germany's Duisburg Intermodal Terminal utilizes IoT and AI technologies to optimize intermodal rail and waterway logistics, supporting the European Union's broader digital and green logistics strategies [6]. In Asia, Singapore's Jurong Logistics Hub integrates autonomous vehicles, AI-driven inventory management, and digital twin technologies, aligning with the country's Smart Nation Vision [7]. In the United States, major logistics providers such as Amazon and UPS leverage robotics, cloud-based platforms, and predictive analytics to streamline fulfillment operations [8]. And in China, digital logistics parks have expanded at an average annual growth rate of 11.7%, contributing to a 20-30 % reduction in logistics costs and a 3-5 % boost to national GDP [9]. Comparable initiatives in emerging economies, including Brazil and Kenya, involve the adoption of digital tools in ports and logistics corridors to improve transparency, alleviate congestion, and facilitate cross-border trade [10].

However, while global examples demonstrate notable benefits, there remains limited academic consensus on how to measure the “smartness” or maturity of logistics parks. Existing evaluations often rely on descriptive case comparisons or fragmented indicators, making it difficult for policymakers and managers to benchmark progress or identify development bottlenecks.

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The rapid transformation of logistics parks and the demonstrated benefits of smart logistics initiatives across regions highlight the need for a systematic framework to evaluate progress, performance, and readiness for future growth. Although digital technologies have driven significant advancements in terms of efficiency, sustainability, and cost reduction, there remains no standardized method for assessing the extent of transformation among logistics parks. Without such evaluation, policymakers and managers face challenges in benchmarking development, identifying gaps, and prioritizing investment strategies. Maturity models offer a structured approach to address this challenge by defining developmental stages and capability levels across specific dimensions [11]. In the context of SLPs, maturity reflects the degree to which digital technologies, intelligent operations, infrastructure, human capital, and sustainability practices have been adopted and optimized. This approach supports evidence-based planning and facilitates comparative assessments across different parks and regions.

Although maturity models have been widely used in domains such as information systems, manufacturing, and smart cities, their direct application to logistics parks is still limited and conceptually fragmented [12]. Existing frameworks present several limitations when applied to SLPs: Many models were developed for broader contexts such as smart cities or general enterprises and thus fail to address the unique structural, operational, and governance features of logistics parks [13], and critical dimensions specific to logistics parks, including platform interoperability, digital public services, and multistakeholder coordination, are frequently overlooked [14]. Furthermore, most available models rely heavily on qualitative assessments or expert scoring, which can introduce subjectivity and limit the comparability of findings [15], while the absence of standardized, data-driven metrics further constrains empirical validation and reduces the practical utility of these models in dynamic logistics environments [16].

To better clarify the research focus, this study distinguishes logistics parks from related entities such as industrial parks and smart cities. Logistics parks are characterized by deeper supply chain integration, logistics service specialization, and dynamic coordination among multiple actors (e.g., logistics firms, customs, transport operators, and digital platform providers) [17]. However, one fundamental issue hindering the development of a fit-for-purpose maturity model is the conceptual ambiguity between SLPs and these related entities. Existing models, often adapted from broader contexts, fail to capture the core operational paradigm and value proposition of a smart logistics park. Unlike smart cities, which prioritize citizen-centric services and urban governance, or smart industrial parks, which focus on manufacturing integration and innovation ecosystems, SLPs are fundamentally defined by their role as integrated nodes within supply chains [18, 19]. Their distinctiveness is characterized by a primary emphasis on the optimization of physical and information logistics flows, the seamless interoperability of platforms connecting shippers, carriers, and warehouses, the automation of core logistics processes (e.g., smart warehousing and autonomous vehicles), and deep integration into global trade and supply chain networks [20]. Consequently, critical SLP capabilities—such as supply chain visibility, freight synchronization, and logistics asset utilization—are frequently underrepresented or entirely absent in maturity models borrowed from other domains. These characteristics necessitate a maturity framework that is fundamentally tailored to, rather than merely adapted for, the logistics park context.

These limitations reveal three research gaps that drive this study: First, there is a lack of integrated maturity models that are not only specifically designed for SLPs but are also conceptually grounded in their unique operational characteristics; second, quantitative criteria for defining and assessing maturity levels remain limited; and third, empirical validation using real-world data from logistics parks is rarely conducted.

In response to these gaps, this study aims to: (1) construct a data-driven and multicriteria maturity model tailored to SLPs; (2) quantify maturity levels across five capability dimensions—economic performance, governance, technological infrastructure, human capital, and environmental sustainability; and (3) empirically validate the model using multisource data from logistics parks in western China. By integrating hierarchical structuring and quantitative evaluation methods, this research contributes to the refinement of maturity assessment approaches and enhances their empirical applicability. The findings are expected to provide both theoretical and practical insights for policymakers, park managers, and researchers seeking evidence-based strategies to accelerate the smart transformation of logistics parks.

2. Maturity models for smart logistics parks

2.1 Distinguishing smart logistics parks from related concepts

Before reviewing maturity models, it is essential to clarify the distinct nature of SLPs and differentiate them from related entities like smart cities and smart industrial parks. While the digital transformation of all three shares common technological enablers (e.g., IoT and AI), their primary objectives, core stakeholders, and key performance concerns differ significantly. SLPs function primarily as integrated nodes within supply chains, focusing on the optimization of logistics flows, warehouse automation, and seamless connectivity among shippers, carriers, and distributors. This stands in contrast to smart cities, which prioritize urban livability and citizen-centric services, and smart industrial parks, which concentrate on manufacturing integration and production innovation. **Table 1** summarizes these critical distinctions, underscoring why maturity models adapted from these contexts are often misaligned with the core operational and strategic realities of SLPs.

Table 1 A comparative analysis of smart logistics parks, smart cities, and smart industrial parks

Feature	Smart Logistics Parks	Smart Cities	Smart Industrial Parks
Primary Objective	To enhance supply chain efficiency, resilience, and connectivity	To improve urban livability, governance, and citizen well-being	To foster industrial production synergy, innovation, and competitiveness
Core Dimensions	Logistics flow optimization, platform interoperability, warehouse & transport automation	Public services, citizen participation, urban infrastructure	Production automation, R&D collaboration, energy management
Key Stakeholders	Logistics service providers, freight companies, retailers	Citizens, government bodies, utility providers	Manufacturers, technology firms, research institutions
Focal Technologies	IoT, AI, Blockchain, Autonomous Vehicles	IoT, Big Data, Digital Government Platforms	Industrial IoT, Digital Twins, Robotics
Assessment Focus	Cargo dwell time, inventory turnover, CO ₂ emissions per ton-km	Service response time, citizen satisfaction, data openness	Production capacity utilization, innovation patents, energy consumption

Data sources: [19, 21-23]

2.2 Foundational maturity models and their evolution

Maturity models originated in the 1980s with the development of the Capability Maturity Model (CMM), which was designed to improve software development processes. The CMM framework outlined five progressive levels, namely Initial, Repeatable, Defined, Managed, and Optimizing, representing increasing organizational capability [24]. This concept later evolved into the Capability Maturity Model Integration (CMMI), which retained the five-level structure while broadening its applicability to general process improvement [25]. These foundational models have influenced the creation of dimension-specific frameworks in Industry 4.0, DevOps, and, more recently, in smart city and industrial park development.

2.3 A critical review of existing models for smart contexts and their limitations for smart logistics parks

In the smart city context, maturity models typically adopt multidimensional frameworks that integrate governance, technology, infrastructure, and sustainability, and use multistage hierarchies to depict progress from basic digitalization to advanced integration. For instance, Cohen's model emphasizes citizen-centered and governance-balanced evolution from Exploring to Transforming [13], while the Forrester model highlights IoT-enabled progression from Static to Autonomous [26]. International frameworks such as ISO 37106:2021 provide globally comparable standards [27], and national models like China's Smart City Maturity Model incorporate policy and planning considerations [28]. Building upon these frameworks, recent studies have developed maturity models for smart and industrial parks, and these models generally assess integration across multiple dimensions such as digital infrastructure, facility management, real-time operations, service ecosystems, and human capital [23, 24]. National initiatives, including China's Smart Park Evaluation System, classify maturity based on digital infrastructure, public service provision, and sustainability [29].

However, as Table 2 illustrates, these models present significant limitations when applied to the SLP context. Their primary focus on urban governance or manufacturing production means they offer inadequate coverage of critical SLP dimensions such as supply chain connectivity, logistics-specific technology coverage, and multistakeholder platform interoperability. Consequently, directly adapting these maturity models to logistics parks may produce biased or incomplete assessments [30].

Table 2 Comparative analysis of existing maturity models and their applicability to smart logistics parks

Model/Framework	Primary Context	Key Dimensions	Strengths	Limitations for SLP Application
Cohen's Smart City Model [13]	Smart City	Governance, People, Economy, Environment	Holistic, emphasizes citizen-centricity	Lacks logistics-specific metrics (e.g., fleet mgmt., warehouse automation)
Forrester Smart City Model [26]	Smart City	Technology, Data, Operations, Experience	Strong on technology, adoption life cycle	Overemphasizes citizen experience, not logistics operational efficiency
ISO 37106:2021 [27]	Smart City	Governance, Economy, Environment, Society	Internationally recognized standard	Too broad, misses SLPs' core functions like supply chain visibility
China's Smart Park Evaluation System [29]	Industrial Park	Infrastructure, Resource Integration, Innovation	Aligns with national industrial policy	Focuses on manufacturing, underrepresents logistics flow optimization

2.4 Emerging maturity models for logistics and persistent gaps

The transformation of traditional logistics parks into SLPs reflects the broader digital evolution of global supply chains and supports real-time monitoring, intelligent decision-making, and platform-based collaboration [31]. Compared with industrial parks, logistics parks involve more complex flows of goods, information, and capital, and require multistakeholder coordination among logistics service providers, transport operators, and customs agencies. Assessing the maturity of SLPs has therefore become increasingly important for research and policy, and several frameworks have emerged to address this need. For example, Chang et al. [32] proposed a life cycle-oriented quality evaluation framework that integrates digitization, intelligence, and environmental performance, while Zhang et al. [33] incorporated carbon emission monitoring into maturity assessments, and Zhu et al. [34] emphasized the importance of government support and policy in the development of digital infrastructure. Liu et al. [14] examined the combined influence of organizational structures and technological practices on maturity progression, and Kryś and Izdebski [35] developed a model focused on structural reliability within logistics centers. However, more recent research has emphasized the role of data-driven approaches and multicriteria decision analysis (MCDA) methods in quantifying performance and reducing subjectivity [31].

Despite these contributions, significant gaps remain, as highlighted in Table 2. Many frameworks are adapted from broader dimensions and therefore fail to capture the distinctive structural, operational, and governance characteristics of logistics parks. Existing models tend to emphasize technology adoption while neglecting the integrated development of governance, human capital, and sustainability dimensions—core capabilities for smart logistics ecosystems. Furthermore, most models rely on qualitative assessments or expert judgment, thereby introducing subjectivity and limiting cross-case comparability. Only a few studies have applied quantitative indicators or validated models with empirical data, making it difficult to verify robustness or practical applicability.

These limitations underscore the need for a robust maturity evaluation model that integrates quantitative metrics, captures the multidimensional nature of SLP development, and can be empirically validated through real-world applications. Such a framework would provide a standardized basis for benchmarking, guide strategic decision-making, and support the sustainable digital transformation of logistics parks.

3. Materials and methods

This study adopts a four-stage research process to develop and validate a maturity evaluation model for SLPs, as illustrated in Figure 1. The first stage, Maturity Framework Formulation, involves identifying and verifying five capability dimensions and 20

subfactors through a combination of a literature review and expert consultation. The second stage, Maturity Level Identification, establishes a four-level structure and defines quantitative criteria for assessing each factor. The third stage, Case Study Evaluation, applies the model to selected logistics parks using empirical data collection and systematic analysis. The final stage, Discussion and Interpretation, compares the case results, synthesizes findings, and derives strategic insights. This sequential process ensures the conceptual robustness and practical applicability of the proposed model.

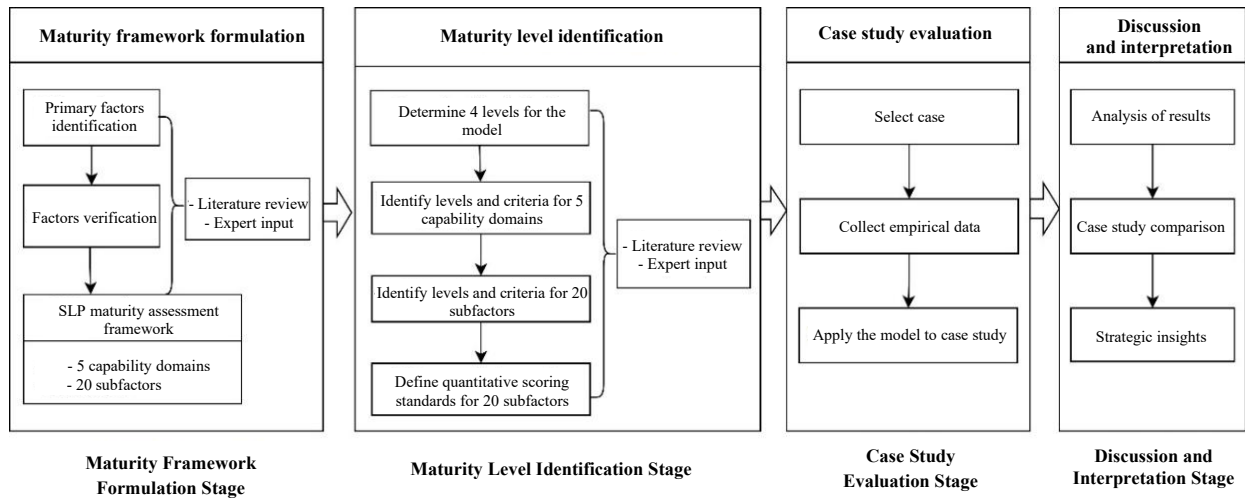


Figure 1 Research flowchart

3.1 Maturity evaluation framework formulation

This study employs a maturity evaluation framework grounded in the dimensions established by [36]. The framework integrates five capability dimensions: Smart Economy, Public Services and Smart Governance, Smart Infrastructure and Intelligent Technology Application, Skilled Human Capital, and Environmental Sustainability. Each dimension is decomposed into certain subfactors, producing a total of 20 measurable indicators, as illustrated in Figure 2. This framework provides a basis for evaluating both the overall and dimension-specific maturity levels, enabling a data-driven assessment of development performance.

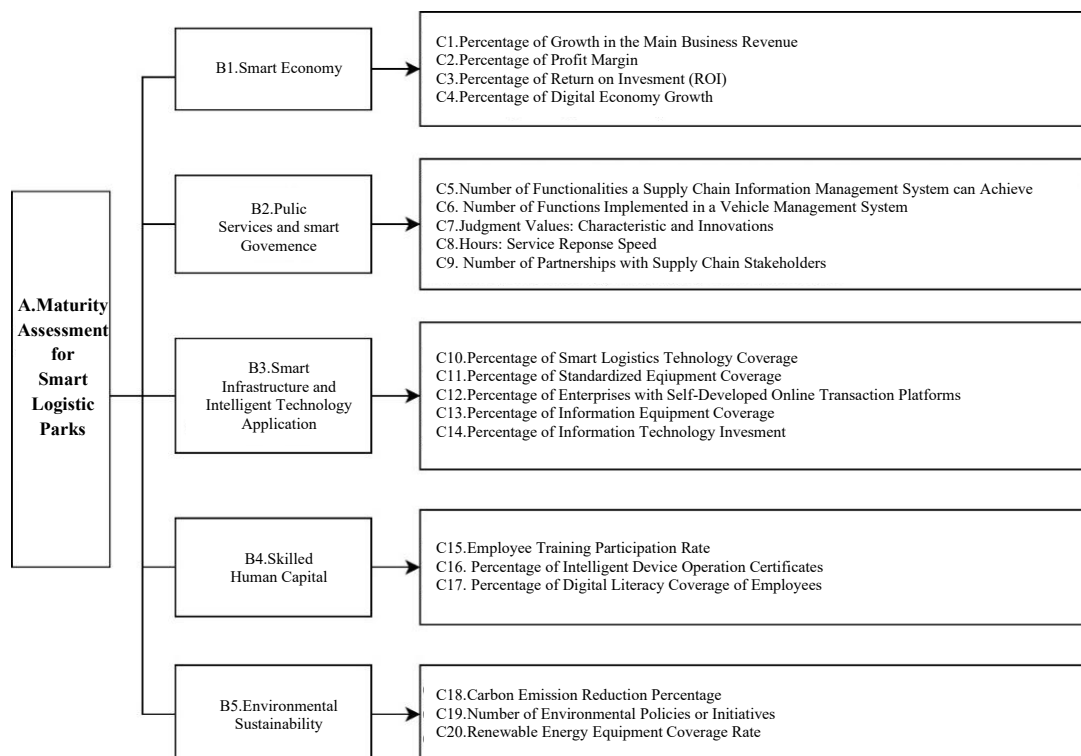


Figure 2 Framework for maturity assessment of the smart logistics parks

3.2 Maturity level identification

Drawing on maturity frameworks for smart cities and industrial parks, along with international standards, industry guidelines, and expert empirical feedback, this study proposes a four-stage classification for SLPs: Initial, Growth, Maturity, and Optimization. These stages correspond conceptually to the widely adopted levels of Initial, Defined, Managed, and Leading [29, 31, 37]. The four-level

framework balances granularity and practicality, allowing clear differentiation between stages while remaining interpretable for practitioners [16, 38]. The classification is depicted in Figure 3, which illustrates the stepwise progression from lower to higher digital and operational capabilities.

- Initial Stage (Level 1): Basic digital infrastructure is established, but integration and automation are minimal.
- Growth Stage (Level 2): Automation and data-driven applications begin to emerge, supporting operational improvements.
- Maturity Stage (Level 3): Intelligent coordination and system integration are achieved, enhancing efficiency and responsiveness.
- Optimization Stage (Level 4): Advanced innovation and sustainability practices are embedded, positioning the park as an industry leader [39].

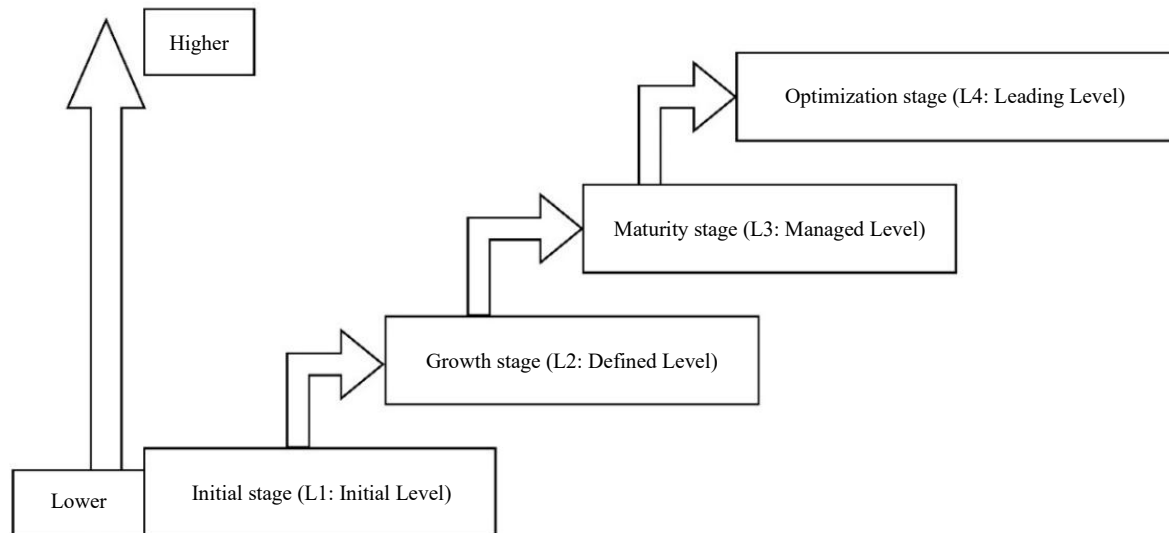


Figure 3 Classification of maturity levels for smart logistics parks

Quantitative scoring criteria for each subfactor were established by drawing on domestic standards, industry reports, white papers, and expert input, which enabled a consistent evaluation across cases. The model provides a transparent and reproducible basis for assessing the digital transformation of SLPs.

3.3 Case selection and data collection

Two logistics parks were selected as empirical case studies to validate the proposed maturity model, with selection criteria including contrasting stages of digital development, representativeness in terms of size and function, and geographical diversity. While the limited number of cases restricts statistical generalization, the approach allows in-depth, exploratory validation of the proposed model. Empirical data were collected from publicly available sources, including government reports, corporate disclosures, websites, and third-party databases, and supplementary insights were obtained through expert consultations and internal documentation where available.

To ensure the reliability and validity of the data, several measures were implemented: First, cross-source verification and temporal consistency checks were conducted during data collection; second, a standardized scoring protocol was strictly followed, and all scores underwent a rigorous expert review process to ensure consistency and minimize subjective bias; and finally, for instances of missing or incomplete data, established imputation rules based on industry benchmarks were applied, supplemented by expert judgment, with all such cases clearly documented to acknowledge potential uncertainties.

3.4 Discussion and interpretation

Collected data were mapped to the 20 subfactors of the maturity model, with each factor being evaluated using predefined criteria and assigned a maturity level ranging from one to four. Final maturity scores for each logistics park were calculated using an unweighted average across the 20 subfactors. This approach favors transparency and interpretability at this model development stage. The unweighted scheme ensures that each factor is evaluated independently, establishing a clear baseline for future refinements involving weighted aggregation. The resulting scores were visualized using radar charts and cross-dimensional profiles, thus facilitating comparative analysis across the five capability dimensions.

The outcomes provide a quantitative foundation for assessing the maturity of SLPs, identifying dimension-specific strengths and weaknesses, and generating strategic insights to guide future digital transformation initiatives.

4. Results

4.1 Maturity model for evaluating smart logistics parks transformation

Building on the maturity framework presented in Figure 2, Table 3 details the stagewise capability characteristics of SLPs. In addition to outlining the general features of each maturity stage, it specifies the corresponding stagewise characteristics for each of the five capability domains. This enables both a holistic and domain-specific understanding of maturity progression.

These stages represent the evolution of SLPs from basic digitization to advanced intelligence, reflecting a continuous enhancement in smart integration and maturity. Smart Economy (B1) transitions from traditional cost control to a profit model driven by smart logistics. At the same time, Public Services and Smart Governance (B2) shifts from conventional regulatory oversight to data-driven,

intelligent decision-making. Smart Infrastructure and Intelligent Technology Application (B3) progresses from manual operations to fully automated and intelligent management. Similarly, Skilled Human Capital (B4) develops from basic skill proficiency to digital management and innovation capabilities. Finally, Environmental Sustainability (B5) transforms from traditional logistics models to a green, low-carbon logistics ecosystem.

Table 3 Stagewise capability descriptions of smart logistics parks' maturity levels

Key Capability Dimensions	Initial Stage (L1: Initial Level)	Growth Stage (L2: Defined Level)	Maturity Stage (L3: Managed Level)	Optimization Stage (L4: Leading Level)	Literature
SLPs' Overall Maturity	Relies on traditional logistics with minimal intelligent technology integration, low digitalization, and outdated infrastructure. Predominantly manual operations and a lack of systematic management hinder efficiency and coordination.	Adopts intelligent technologies, improving efficiency and standardizing management, but digitalization and collaboration remain limited.	Leverages advanced digital technologies for efficient management, optimizing economic, social, and environmental outcomes. Strong intelligent collaboration, with room for further refinement.	Operates at a globally leading level with an intelligent, sustainable, and collaborative system, driving industry innovation and competitiveness.	[11, 31, 40]
B1. Smart Economy	Low financial benefits and efficiency due to reliance on traditional logistics and the absence of data-driven optimization.	Initial digital adoption improves financial performance, but economic efficiency remains suboptimal.	Digitalization boosts financial benefits, reduces costs, and enhances efficiency.	Optimizes financial performance and ensures efficient economic collaboration.	[23, 41]
B2. Public Services and Smart Governance	Traditional infrastructure and management limit intelligence, efficiency, and service quality.	Digital tools improve service quality, but coordination challenges persist.	Intelligent systems enhance logistics efficiency and service quality.	Intelligent management enables real-time optimization, ensuring coordinated logistics and optimal service quality.	[42-44]
B3. Smart Infrastructure and Intelligent Technology Application	Logistics infrastructure exists but lacks intelligence and digitalization, relying on manual operations.	Adopts smart warehousing and transport monitoring, but automation and digitalization remain limited.	Extensive use of intelligent systems optimizes operational efficiency.	Intelligent operations utilize AI, 5G, and blockchain for autonomous decision-making and optimization.	[2, 42, 45]
B4. Skilled Human Capital	The workforce lacks expertise in intelligent logistics and innovation capacity.	Intelligent logistics talent was introduced, but the workforce remains largely traditional.	Experts in intelligent logistics management and technology foster innovation.	A high-level intelligent logistics talent ecosystem drives innovation and industry advancement.	[42, 46]
B5. Environmental Sustainability	Limited focus on sustainability, with high energy consumption, significant emissions, and low resource efficiency.	Adopts energy-efficient equipment and low-carbon transport, but sustainability needs improvement.	Minimizes energy use and emissions through green logistics, ensuring economic and environmental balance.	Achieves carbon neutrality or near-zero emissions, developing a globally leading sustainable logistics system.	[23, 29]

Table 4 details the maturity level descriptions and quantitative thresholds for each subfactor. These thresholds, shown in parentheses, ensure a consistent and measurable classification across the four maturity stages. Their derivation followed a prioritized protocol: Domestic and international standards were considered foremost, followed by recognized industry practices and best-practice benchmarks. For unavailable key indicators, substitute values were judiciously drawn from related domains such as smart cities and industrial parks. The entire framework was refined through post-COVID, data-driven analysis and underwent cross-source verification and expert review to mitigate bias and enhance reliability. As a result, this scoring system provides a quantitative, reproducible, and comparable basis for assessing SLPs.

Table 4 Maturity level descriptions and thresholds for smart logistics parks subfactors

Subfactor	Initial Stage (L1: Initial Level)	Growth Stage (L2: Defined Level)	Maturity Stage (L3: Managed Level)	Optimization Stage (L4: Leading Level)	Literature
C1. Percentage of Growth in the Main Business Revenue	Slow growth, mainly relies on the traditional model. (<12%)	Moderate growth, partial digital adoption. (12-18%)	Notable growth, improved efficiency via digital management. (18-20%)	Rapid growth, driven by smart tech & big data. (>20%)	[47, 48]
C2. Percentage of Profit Margin	Low profit, due to high logistics costs. (<8%)	Moderate increase, via basic supply chain optimization. (8-12%)	Visible improvement through intelligent optimization systems. (12-15%)	High profit via advanced data-driven operations. (>15%)	[47, 49]
C3. Percentage of Return on Investment (ROI)	Low ROI with traditional investments. (<15%)	Moderate ROI improvement from partial tech upgrades. (15-18%)	Considerable ROI growth from intelligent systems. (18-20%)	Maximized ROI via advanced data-driven strategies. (>20%)	[48, 50]
C4. Percentage of Digital Economy Growth	Underdeveloped digital economy. (<25%)	Slow growth with initial tech adoption. (25-35%)	Significant growth via digital transformation. (35-40%)	Exceptional growth from advanced digital technologies. (>40%)	[47, 48, 51]
C5. Number of Functionalities a Supply Chain Information Management System can Achieve	Limited functionalities for basic warehouse operations. (<20)	Basic inventory & order management with limited financial analysis. (20-38)	Supports reverse logistics, warehouse management, transport tracking, & real-time analysis. (38-40)	AI and blockchain systems enable full supply chain intelligence and automated decisions. (>40)	[14, 42]
C6. Number of Functions Implemented in a Vehicle Management System	Manual vehicle management with limited tracking. (<15)	Smart scheduling with GPS tracking and basic automation. (15-28)	AI-driven route planning, fuel monitoring, and predictive maintenance. (28-30)	Fully automated management via autonomous driving and real-time scheduling. (>30)	[52]
C7. Judgment Values: Characteristics and Innovations	Traditional management with limited innovation. (<1.5)	Early intelligent decision-making, innovation limited. (1.5-3.0)	Intelligent decision-making with ongoing innovation. (3.0-3.5)	AI-driven decisions with industry-leading innovation. (3.5-4.0)	[43, 52]
C8. Hours: Service Response Speed	Slow service response, resulting in operational inefficiency. (>4)	Initial automation provides moderate improvement in response speed. (1-4)	Smart systems enhance operational efficiency and reduce service delays. (0.5-1)	AI- and IoT-enabled real-time response ensures optimal operational efficiency. (<0.5)	[40, 53]
C9. Number of Partnerships with Supply Chain Stakeholders	Minimal cooperation among supply chain stakeholders. (<100)	Initial collaboration established but remains limited. (100-450)	Strong partnerships enable efficient supply chain integration. (450-500)	Globally connected network optimizes cross-industry collaboration. (>500)	[14, 29]
C10. Percentage of Smart Logistics Technology Coverage	Reliance on traditional logistics with minimal digital use. (<60%)	Initial digital investment with limited application. (60-85%)	Intelligent technologies notably improve efficiency. (85-90%)	AI- and big data-driven optimization at an industry-leading level. (>90%)	[54, 55]
C11. Percentage of Standardized Equipment Coverage	Low adoption. (<50%)	Gradual introduction. (50-85%)	Widespread implementation. (85-90%)	Fully standardized, highly automated. (>90%)	[40, 54]
C12. Percentage of Enterprises with Self-Developed Online Transaction Platforms	Few enterprises develop platforms. (<15%)	Some develop platforms for transformation. (15-25%)	Most use smart transaction platforms. (25-30%)	Fully integrated online systems. (>30%)	[54]

Table 4 (continued) Maturity level descriptions and thresholds for smart logistics parks subfactors

Subfactor	Initial Stage (L1: Initial Level)	Growth Stage (L2: Defined Level)	Maturity Stage (L3: Managed Level)	Optimization Stage (L4: Leading Level)	Literature
C13. Percentage of Information Equipment Coverage	Low adoption. (<75%)	Partial adoption. (75-90%)	High coverage ensuring connectivity. (90-95%)	Fully automated smart systems. (>95%)	[42, 54]
14. Percentage of Information Technology Investment	Minimal investment. (<25%)	Initial targeted investments. (25-35%)	Large-scale intelligent system investment. (35-40%)	Continuous cutting-edge IT investment. (>40%)	[40, 54]
C15. Employee Training Participation Rate	Minimal training. (<50%)	Partial training. (50-80%)	Most staff trained in smart logistics. (80-85%)	Comprehensive training system. (>85%)	[14, 37]
C16. Percentage of Intelligent Device Operation Certificates	Few certified. (<60%)	Some certified. (60-85%)	Majority certified. (85-90%)	Fully certified workforce. (>90%)	[36]
C17. Percentage of Digital Literacy Coverage of Employees	Low proficiency. (<65%)	Partial training. (65-85%)	Most staff digitally competent. (85-90%)	Fully digitally skilled workforce. (>90%)	[36]
C18. Carbon Emission Reduction Percentage	High emissions. (<25%)	Partial automation reduces emissions. (25-40%)	Smart tech significantly cuts emissions. (40-45%)	Fully AI-driven optimization. (>45%)	[55, 56]
C19. Number of Environmental Policies or Initiatives	Few policies. (<15)	Basic measures. (15-30)	Systematic green strategies. (30-35)	Comprehensive sustainability leadership. (>35)	[40, 55]
C20. Renewable Energy Equipment Coverage Rate	Minimal adoption. (<40%)	Partial implementation. (40-70%)	Integrated solar/wind power. (70-75%)	Full renewable strategy. (>75%)	[54, 55]

4.2 Smart logistics parks transformation evaluation

The locations for both case studies are in the same industrial city in western China, a region that exhibits a moderate level of economic development and is actively promoting digital logistics initiatives. Selecting cases from this shared locale provides a controlled comparative environment, as the potential influence of broad regional policy differences is minimized. Logistics Park 1 (LP1) was redeveloped from former warehouse facilities into a steel distribution hub and now specializes in bulk material trade and storage. The park currently manages approximately five million tons of cargo annually, representing 18% of the local market share. LP1 is categorized as a transitional logistics park, as it is in the process of shifting from traditional to digital logistics operations. The park maintains an occupancy rate above 90% and achieved a transaction volume exceeding CNY50 million in 2022.

Logistics Park 2 (LP2) is strategically located near an inland river port with multimodal access to road, waterway, and rail networks. The park focuses on steel processing and intelligent supply chain services, supported by a smart logistics cloud platform that facilitates end-to-end digital management. This platform has improved cargo circulation efficiency by 62% and significantly reduced operational costs. Hosting more than 130 enterprises, LP2 demonstrates pronounced industrial clustering effects. Recognized as a national model logistics park in 2021, LP2 achieved revenue exceeding CNY10 billion in the following year. LP2 is an “emerging” smart logistics park with foundational smart technologies, representing the early growth stage of development.

By selecting LP1 and LP2, which represent different stages of digital transformation, this study demonstrates the applicability and usefulness of the proposed maturity evaluation model in differentiating between transitional and emerging SLPs, thereby highlighting its diagnostic and benchmarking capabilities.

Table 5 summarizes the empirical data mapped to maturity thresholds, thus enabling cross-domain comparison, while Figures 4 and 5 visualize factor-level and aggregated dimension-level maturity profiles.

The comparative findings reveal that in the economic dimension, LP1 demonstrates a slight advantage in terms of main business revenue growth and return on investment, reflecting residual strengths associated with traditional logistics operations. In contrast, LP2 achieves higher profit margins and stronger digital economy growth, indicating greater efficiency and economic benefits derived from digital transformation. Notwithstanding these differences, both parks remain positioned at the boundary between the Initial (L1) and Growth (L2) stages, suggesting that their financial and digital integration is still in the early stages of development.

Table 5 Summary of data for the logistics parks

Dimensions	Factors	LP1			LP2		
		Empirical Data	Factor Level	Dimension Level	Empirical Data	Factor Level	Dimension Level
B1. Smart Economy	C1. Percentage of Growth in the Main Business Revenue	8.30%	1	1.5	8.10%	1	1.5
	C2. Percentage of Profit Margin	10.40%	2		10.50%	2	
	C3. Percentage of Return on Investment (ROI)	9.20%	1		8.90%	1	
	C4. Percentage of Digital Economy Growth	25.10%	2		27.30%	2	
B2. Public Services and Smart Governance	C5. Number of Functionalities a Supply Chain Information Management System can Achieve	21	2	2	16	1	2
	C6. Number of Functions Implemented in a Vehicle Management System	15	2		15	2	
	C7. Judgment Values: Characteristics and Innovations	3.20	3		3.00	3	
	C8. Hours: Service Response Speed	4	1		2	2	
B2. Public Services and Smart Governance	C9. Number of Partnerships with Supply Chain Stakeholders	150	2		120	2	
B3. Infrastructure and Intelligent Technology Application	C10. Percentage of Smart Logistics Technology Coverage	42.60%	1	1	48.70%	1	1.6
	C11. Percentage of Standardized Equipment Coverage	49%	1		51%	2	
B3. Infrastructure and Intelligent Technology Application	C12. Percentage of Enterprises with Self-Developed Online Transaction Platforms	12.60%	1	1	16.00%	2	1.6
	C13. Percentage of Information Equipment Coverage	61.30%	1		76.00%	2	
	C14. Percentage of Information Technology Investment	12.70%	1		12.00%	1	
B4. Skilled Human Capital	C15. Employee Training Participation Rate	54.60%	2	1.33	54.30%	2	1.67
	C16. Percentage of Intelligent Device Operation Certificates	59.70%	1		57.00%	1	
	C17. Percentage of Digital Literacy Coverage of Employees	60.70%	1		67.90%	2	
B5. Environmental Sustainability	C18. Carbon Emission Reduction Percentage	20.00%	1	1.67	19.70%	1	1.67
	C19. Number of Environmental Policies or Initiatives	15	2		15	2	
	C20. Renewable Energy Equipment Coverage Rate	41.00%	2		42.80%	2	
Overall Maturity Level			1.5			1.7	

The comparative analysis of LP1 and LP2 across the five capability dimensions reveals distinct strengths and areas for improvement. In the smart economy dimension, LP1 demonstrates a slight advantage in main business revenue growth, suggesting that transitional logistics parks can still retain volume-based benefits. However, LP2 achieves a higher profit margin, reflecting greater economic efficiency associated with smart logistics operations. LP1 also outperforms LP2 in return on investment, indicating more effective capital utilization, while LP2 exhibits stronger digital economy growth, underscoring the economic benefits of digitalization.

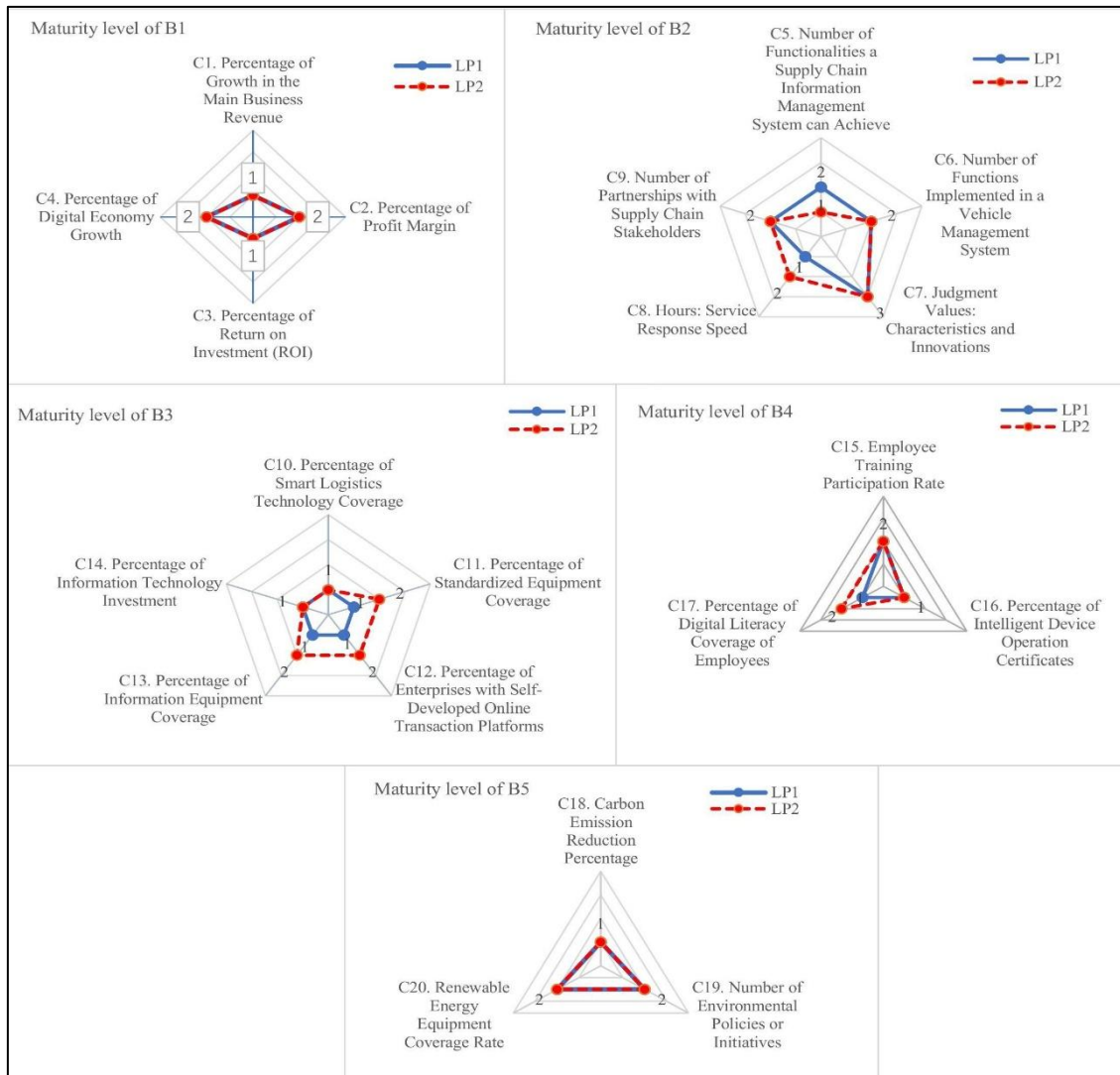


Figure 4 Factor-level maturity for logistics parks

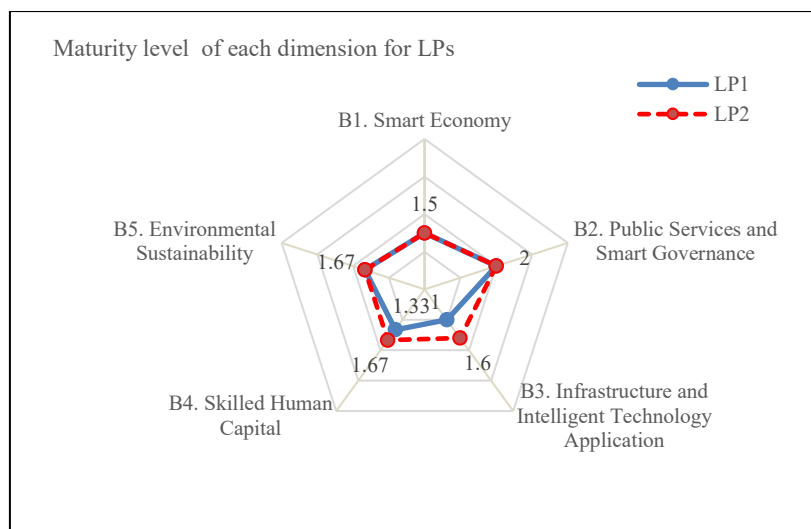


Figure 5 Dimension-level maturity for logistics parks

In the dimension of public services and smart governance, LP1 provides broader functional coverage within its supply chain information management system and maintains a larger number of partnerships with supply chain stakeholders, thereby suggesting stronger network integration. Both parks perform similarly in vehicle management functionalities and innovation characteristics; however, LP2 demonstrates a notably faster service response time, which enhances its operational responsiveness. When evaluated against the maturity thresholds, this dimension reaches the Growth stage in both parks, with innovation emerging as the most advanced factor, achieving Level 3 maturity.

Differences are more pronounced in the infrastructure and intelligent technology application dimension. LP2 slightly outperforms LP1 in smart logistics technology coverage, standardized equipment adoption, and the development of self-owned online transaction platforms, indicating a more advanced technological foundation. LP1 remains largely at the Initial stage across this dimension, while LP2 has progressed toward the early Growth stage, reflecting initial standardization and integration of intelligent systems.

The skilled human capital dimension shows that both parks have similar employee training participation rates, but their strengths differ in focus. LP1 demonstrates a higher proportion of employees certified in intelligent device operations, while LP2 exhibits higher levels of digital literacy, suggesting better preparedness for advanced logistics software and technology. Mapping these results to maturity thresholds indicates that LP1 is positioned slightly above Level 1 and LP2 approaches Level 2, revealing incremental but uneven human capital development between the two parks.

The environmental sustainability dimension indicates that LP1 achieves marginally higher carbon emission reduction rates, while LP2 has greater coverage of renewable energy equipment. The two parks have implemented a comparable number of environmental policies and initiatives, resulting in similar maturity scores at approximately Level 1.7, which reflects early adoption of sustainability practices, with considerable potential for further enhancement, particularly in measurable environmental outcomes such as carbon reduction.

When viewed holistically, the overall maturity level of LP1 is 1.5 and that of LP2 is 1.7, placing both between the Initial and Growth stages. LP2's slightly higher maturity score is largely attributable to its more advanced technological infrastructure and stronger digital skill base, whereas LP1 continues to maintain advantages in terms of traditional economic performance and stakeholder partnerships. These complementary profiles highlight how the proposed maturity model effectively distinguishes between transitional and emerging SLPs, demonstrating its value as a diagnostic tool for benchmarking and guiding strategic development pathways.

5. Discussion

The comparative analysis reveals that the distinct maturity profiles of LP1 and LP2 are influenced by their contrasting strategic positioning, a factor emphasized in logistics transformation studies [5]. LP1's strength in operational ROI and supply chain functionality originates from its bulk material trade role, which relies on scale and asset utilization rather than digital innovation [57]. Conversely, LP2's higher scores in digital infrastructure and service responsiveness result from its strategic vision as an intelligent supply chain service provider, which necessitates upfront technology investment. External policy support further explains this divergence, as LP2's national model park status facilitated resource access, underscoring the role of government intervention in technology adoption [58]. This observation demonstrates that the transformation of SLPs is nonlinear, context-dependent, and path-sensitive, in line with Alavi-Borazjani et al. [59]. Both parks fall between the Initial and Growth stages, below L3 and L4 thresholds—a pattern observed in inland and developing regions [60, 61].

The dimension-specific analysis reveals systematic gaps. Both parks exhibit low smart economy maturity, relying on volume-based growth instead of efficiency or innovation-driven models [41]. LP2's modestly higher digital economy growth, however, suggests the initial adoption of efficiency-oriented tools. Public Services and Smart Governance shows relatively higher maturity, with characteristics and innovations at Level 3; however, fragmented digitalization and uneven service responses reveal persistent siloed practices and underdeveloped governance [43]. LP2's advanced digital infrastructure contrasts sharply with LP1's lag, due to funding or strategic constraints—in line with observed inland–port disparities [61, 62] and highlighting how infrastructure directly shapes transformation paths. Both parks lack structured talent pipelines, and LP2's digital literacy advantage alone cannot compensate for this, underscoring a system-wide need for coordinated workforce development strategies [1]. Environmental Sustainability exhibits nearly uniform scores, reflecting policy commitments that lack tangible outcomes, particularly in terms of emission reduction—a challenge consistent with national trends [63]. This gap highlights the need for practical measures such as carbon tracking and renewable energy integration.

The identified maturity gaps provide clear guidance for stakeholders to accelerate the smart transformation of logistics parks. For policymakers, priorities include: (1) targeted funding for digital infrastructure, especially for less mature parks, as such focused investment has proven effective in bridging regional digital divides [60]; (2) establishing regional skills programs for logistics automation, addressing the critical human capital gap identified in this study and supported by workforce development literature [64]; and (3) implementing concrete measures like carbon tracking, renewable energy integration, and environmental auditing systems [56]. For park managers, strategies should align with maturity levels. LP1 should adopt modular digital tools to enhance existing operations—an incremental approach recommended for traditional logistics operators [5]. Meanwhile, LP2 should focus on optimizing returns from its technological investments through advanced analytics and piloting green initiatives to build competitive advantage. This stakeholder-specific approach enables coordinated planning and makes the maturity model a practical tool for guiding digital transformation across different park contexts.

The proposed maturity model serves as both a benchmarking tool and a development roadmap, integrating quantitative metrics with multidimensional assessment to evaluate the transformation of SLPs. It provides practical value by enabling policymakers to monitor regional progress toward strategic goals, assisting park managers in planning targeted upgrades, and offering researchers a structured foundation for systematic comparative studies.

This study has several limitations that point towards valuable research directions. The model's validation on two inland Chinese parks constrains the generalizability to coastal or international contexts, warranting future studies with larger, more diverse samples and cross-regional comparisons. While an expert review and protocols were used, the scoring of qualitative factors (e.g., C7) retains some subjectivity; hence, future work could develop more detailed scoring rubrics or explore NLP-based automated scoring. While unweighted aggregation does not account for differing factor importance, it provides a clear baseline for model validation. Future research could explore weighted scoring or sensitivity analysis to assess the influence of relative importance on overall maturity rankings. Finally, longitudinal tracking is needed to understand maturity progression, and regular updates will be essential to keep pace with technological evolution [31].

6. Conclusion

This study establishes a structured maturity model that addresses the gap in standardized evaluation methods for transforming SLPs. Departing from qualitatively dominated or generically adapted approaches, the model introduces a unified framework integrating five core dimensions with quantifiable metrics across four maturity levels.

The principal contribution of this work is threefold. Theoretically, it advances maturity modeling in logistics by establishing a unified framework that integrates smart economy, governance, technology, human capital, and sustainability into a single assessment system; methodologically, it provides researchers with a validated tool for systematic comparative and longitudinal studies; and practically, it offers stakeholders a scalable framework for guiding strategic planning and resource allocation in digital transformation initiatives.

Future work should focus on validating the model's generalizability across diverse geographical contexts, refining the assessment mechanism through weighted scoring systems, and tracking maturity progression through longitudinal studies. As logistics parks continue to evolve as critical nodes in global supply chains, this model provides a foundation for promoting intelligent, resilient, and sustainable development pathways.

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