

Guiding digital transformation in logistics: A conceptual framework grounded in Design Science methodology

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Abstract. Digital transformation in the logistics sector is often guided by instinctive responses to market shifts rather than structured, criteria-based planning.: This study investigates how a conceptual framework for digital transformation can support logistics companies—particularly freight forwarders—in making informed, strategic decisions when adopting Transport Management Systems (TMS). Rather than treating digital tools as isolated technological upgrades, the framework emphasizes the importance of aligning system functionalities with both the internal conditions of the organization and the broader external environment, including market, regulatory, and technological factors. To evaluate the robustness of the framework, a practical example is presented involving the selection of a TMS through the application of the developed methodology. The findings suggest that the framework offers strong potential in helping logistics firms navigate the complexity of TMS selection, especially in contexts where internal needs and external pressures intersect. By bridging company-specific requirements with market-facing functionalities, the framework fosters better alignment between digital tools and strategic goals. This research offers a structured yet adaptable approach for researchers who can build upon the conceptual model while practitioners, seeking to guide digital transformation through informed, context-sensitive evaluation may find the results promising if still needing further empirical testing. In doing so, it contributes a practical decision-support model for enhancing the long-term effectiveness of technology adoption in freight forwarding operations.

Keywords: Digital logistics, SaaS integration, Transport Management Systems, Selection process, Platform interoperability

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Introduction

Effective supply chain management (SCM) ensures the seamless movement of goods from producers to consumers through procurement, production, and distribution. It involves multiple actors—suppliers, manufacturers, distributors, retailers, and customers—whose performance is evaluated by cost, lead time, and quality. Although logistics functions remain stable, digital technologies have replaced manual processes, increasing transparency and efficiency [1]. Rising competition drives logistics providers to innovate, with the Transport Management System (TMS) emerging as a central digital hub connecting supply chain operations. The growth of “asset-light” logistics models further emphasizes the need for robust digital infrastructures. Despite its benefits, TMS adoption faces obstacles such as high costs, complex integrations, limited flexibility, poor user experience, and outdated technologies [2][3]. Selecting a TMS aligned with organizational needs is thus essential. Current research rarely

integrates platform interoperability with business strategy, overlooking alignment between goals, functionality, and readiness. This study proposes a conceptual framework for digital transformation in logistics, aligning technology adoption with organizational capabilities. Its key contributions are: (1) an Analytic Network Process (ANP)-based decision framework for solving multi-criteria decision-making (MCDM) problems in TMS selection, and (2) a step-by-step example demonstrating its practical use. The paper proceeds as follows: Section II reviews TMS selection literature, Section III defines the problem, Section IV outlines the ANP framework, Section V presents its application, and Section VI concludes with findings and implications.

Literature review

A systematic literature review was conducted to identify methodological gaps, synthesize findings, and derive practical insights. The central research question was: Which methodologies are employed in selecting Transport Management System (TMS) platforms in logistics? The review examined studies from 2020–2025 addressing SaaS-based TMS selection, using the Scopus database with the keywords logistics, selection, SaaS, and TMS. Only English-language, peer-reviewed studies on SaaS logistics applications were retained; theoretical-only and grey literature were excluded. The review indicates that while most studies aim to align software selection with organizational objectives, heterogeneous methods and firm-specific contexts hinder a unified approach. Selection is generally conceptualized as a Multi-Criteria Decision-Making (MCDM) problem [4], predominantly applying the Analytic Hierarchy Process (AHP) [5]. However, AHP's hierarchical structure neglects interdependencies among criteria, prompting adoption of the Analytic Network Process (ANP). Although MCDM techniques are prevalent in domains such as construction and energy, their systematic application to software selection remains limited. Extensions include MCDM use in Software Project Management (SPM)—notably AHP for tool evaluation [4] and fuzzy logic to accommodate uncertainty [6–8]. More sophisticated approaches encompass Goal-Question-Metric (GQM)-based models [9], Product Lifecycle Management (PLM) selection frameworks [10], and fuzzy or grey-based ERP models [6,11,12]. Despite these advances, comprehensive, dependency-sensitive approaches for complex software remain scarce. Insights from ERP selection research are instructive due to analogous challenges of uncertainty, user resistance [13], infrastructure constraints, and cost considerations [14]. To address these deficiencies, this study introduces a Design Science Research (DSR)-based conceptual framework that integrates internal and external organizational factors via the Analytic Network Process (ANP), enabling a more holistic, interdependency-aware methodology for TMS selection.

Methodology

According to [15], Design Science Research (DSR) starts with problem identification and theoretical insight development. Literature shows many software selection studies exist, but few focus on TMS or integrate both external and internal contexts; ERP research often overlooks these dimensions, highlighting the need for a comprehensive framework. As [15] describes, DSR iteratively constructs and evaluates artifacts, including models, frameworks, architectures, and implementations, assessing each artifact individually and relative to prior iterations. Its strength lies in producing implementable, empirically testable artifacts that refine existing solutions and generate generalizable insights [15], making it suitable for holistic TMS selection. The DSR Knowledge Contribution Framework categorizes contributions by problem and solution maturity: improvement (enhancing solutions), exaptation (adapting methods), innovation (applying known methods to new problems), and invention (creating new solutions), guiding artifact design and framing academic and practical significance.

Table 1. Contribution of the study according to the Design Science Research (DSR) Knowledge Contribution Framework

Problem Domain	Solution Domain	Contribution Type	Concrete Example
Known	Known	Improvement	Enhancing the ANP-based software selection method by integrating internal and external company variables to optimize Transport Management System (TMS) selection using a refined, proven approach.
Known	New	Exaptation	Applying the ANP method—traditionally used for operational software tool selection—to strategic-level decisions in Transport Management System (TMS) selection.

Source: Authors' own research

Proposed framework

This study employs an Analytic Network Process (ANP) framework for TMS selection, accommodating interdependent criteria and feedback loops using qualitative and quantitative pairwise comparisons. As noted in [5], ANP involves four stages: first, clarifying the objective and decision goal, e.g., selecting a TMS aligned with operational and strategic needs; second, structuring elements—goals, criteria, sub-criteria, and alternatives—and performing pairwise comparisons via Saaty's scale to capture interdependencies through eigenvalue-based priority vectors; third, constructing the Supermatrix to aggregate influence weights and feedback among elements; and fourth, normalizing the supermatrix to rank TMS platforms based on holistic performance. Building on this, a seven-step, customized ANP framework for TMS evaluation is proposed (Figure 1).

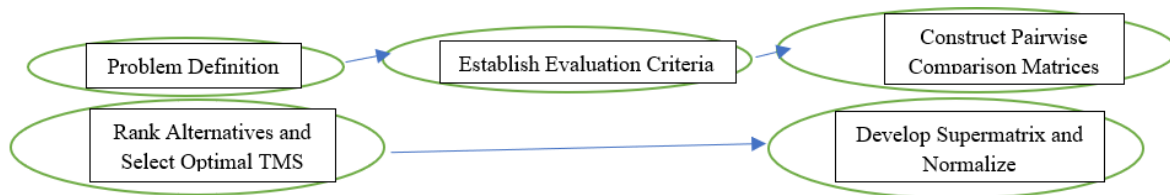
ANP Framework for TMS Selection

Choosing a TMS involves balancing internal organizational needs and external influences. ANP supports this by integrating qualitative judgments and feedback among decision elements—superior to AHP for handling interaction across technical, organizational, and environmental dimensions [4]. The process starts by defining the problem: selecting the optimal TMS based on organizational and external factors. Evaluation criteria are grouped into internal ones, referring to process complexity, integration, scalability, IT setup, structure, and product types (e.g., perishable, bulky) and external ones defined by a PESTEL analysis [16] containing the criteria of: political (regulations), economic (cost), social (skills), technological (IoT), environmental (emissions), legal (compliance). Furthermore, the framework uses a 'Market Factor Score' defined by the formula $\text{Market Score} = \text{DB Score} \times \text{CPI \%}$ where the DB Score is extracted from World Bank Doing Business 2020 [15], and CPI from the 2024 Corruption Perception Index [17]. This emphasizes automation and compliance where needed. The decision elements (goals, criteria, sub-criteria, and vendors) are structured in a network. Experts compare elements using Saaty's 1–9 scale. Comparisons populate a supermatrix that models interdependencies (e.g., budget constraints influenced by economic conditions). The normalized matrix yields global priority scores, used to rank vendors by best organizational fit.

Modeling TMS Selection as an MCDM Problem

TMS selection is treated as a Multi-Criteria Decision-Making (MCDM) problem, evaluating platforms across strategic, operational, and technical criteria. These are classified as internal (logistics needs, e.g., perishables; scalability; software compatibility; coverage; structure) and external, following the PESTEL framework (regulatory, economic, social, technological, environmental, legal). Formally, let $T = \{T_1, \dots, T_n\}$ denote the TMS options and $C = \{C_1, \dots, C_m\}$ the criteria. The objective is to select the optimal TMS, T^{opt} , that maximizes fulfillment across all C_j . A decision matrix A ($M \times N$) is defined, with rows as criteria C_j , columns as alternatives T_i , and elements $a_{ij} \in A$ representing T_i 's performance on C_j . Each criterion C_j is weighted W_j via pairwise comparisons (e.g., Saaty scale [20]) or expert input, with weights adaptable to organizational or market changes. The selection process proceeds in four steps: formulate evaluation criteria reflecting internal structure, strategic goals, and macro-environmental pressures; map these to candidate TMS functionalities; construct a weighted decision matrix; and apply an MCDM method, such as ANP or MACBETH, to derive the ranking of alternatives.

Figure 1. Overview of the TMS Selection Process Using ANP



Source: Authors' own contribution

Results and further discussions

The framework tackles SPM complexities by managing interdependencies and feedback, areas where AHP and ANP often fall short [5; 9]. It integrates macro- and micro-environmental factors beyond standard technical and financial criteria [7; 10], ensures logical coherence and reliability [8], incorporates comprehensive criteria, and adapts to varying project scales [7; 10]. A limited scenario in the next section illustrates its real-world application.

Applied Case Example: Selecting a TMS Platform

This section illustrates the proposed framework for solving an MCDM problem—selecting the optimal TMS. Oracle TM, SAP TM, and MercuryGate are evaluated using publicly available features. A fictional company is modeled, with each internal and external characteristic assigned a binary score from 0 to 1.

Table 2. Company profile matrix example

Company Factor	Score (0-1)	Formula Used
Company size (multiple locations etc.)	1	$Score \in [0, 1]$
Company geographical spread	0	$Score \in [0, 1]$
Pre-existing software ecosystem	0	$Score \in [0, 1]$
Degree of partner collaboration	1	$Score \in [0, 1]$
Product characteristics	0	$Score \in [0, 1]$

Source: Authors' own research

This aids in defining selection criteria, encompassing internal needs (e.g., logistics features, IT infrastructure, scalability) and external drivers (e.g., regulatory, technological, market trends per the PESTEL model). Then a 'Market Factor Score' is used to describe the market of the adopting company as its external environment. This is calculated as: Market Score = DB Score $\times$ (CPI %) Where: DB Score = World Bank Doing Business 2020 score and CPI = Transparency International's 2024 Corruption Perception Index (as a %). In our case we obtain the following results:

Table 3. Market score matrix example

Country	DB Score	CPI (%)	Market Score	Formula Used
Germany	79,7	80	63,76	$MFS = DB \times (CPI \div 100)$
France	76,8	72	55,296	
Italy	72,3	56	40,488	
USA	84	69	57,96	
China	77,9	42	32,718	
India	71	40	28,4	

Source: Authors' own research

The score determines how aggressively a company should pursue automation and regulatory functionalities in its TMS. Evaluation criteria are structured into three interrelated clusters: operational and technical features (integration, visibility, automation), strategic fit and organizational alignment (adaptability, workflows), and external environment and compliance (regulations, responsiveness, sustainability) (see Table 5) [2][3]. Candidate TMS platforms are identified based on industry adoption, functional scope, and usage, with Oracle Transportation Management (OTM), SAP TM, and MercuryGate TMS selected illustratively. An Analytic Network Process (ANP) model captures interdependencies among decision factors. Table 5 maps intra- and inter-cluster interactions, and feature importance is quantified using the Saaty 1–9 ratio scale, providing a structured, dependency-aware framework for TMS selection [2][3].

Table 4. Interaction of decision elements within and across clusters according to Saaty Fundamental Scale

Intensity	Definition	Interpretation
1	Equal importance	Two elements are equally preferred or influential
3	Moderate importance	One element is slightly more influential than the other
5	Strong importance	One element is clearly more important
7	Very strong importance	One element is strongly favored and proven through experience
9	Extreme importance	One element is absolutely more important
2, 4, 6, 8	Intermediate values	Used for compromise between adjacent judgments
1/x (e.g., 1/3, 1/5)	Reciprocal values	Reflects the inverse importance when switching the elements

Source: Akbar, S. et al. (2023)

This scale forms pairwise comparison matrices for criteria and alternatives, from which priority vectors are derived using eigenvalue methods. Step six involves conducting these pairwise comparisons, either manually or with software such as Super Decisions, which calculates priority weights. Company factor scores are mapped to TMS technical and functional features via predefined logic. For instance, firms with low technical expertise should emphasize cloud hosting, automation, and ease of use, while 3PLs prioritize carrier connectivity and freight cost management. These relationships define the importance weights of TMS functionalities (e.g., Company_to_Tech_Weights, Company_to_Func_Weights; Appendix B). Feature weights are adjusted by Market Factor Scores using: $\text{Adjusted Weight} = \text{Company Weight} \times (0.5 + 0.5 \times \text{Normalized Market Score})$. This scales weights between 0.5 and 1.0, providing conservative estimates for complex or low-transparency markets. Next, users assess each TMS feature's support level (0 = not supported, 1 = fully supported) (Appendix B). The final score per TMS is: $\text{Score}_{\text{TMS}} = \sum(W_f \times S_f)$ where W_f is the feature weight and S_f the support score. After forming the weighted supermatrix, it is raised to powers until convergence, yielding final priority weights for each TMS platform. The highest score indicates the optimal TMS for the company's profile and environment.

Table 5 Grouping of the features of the three TMS platforms into clusters :

Cluster Name	Feature	Symbol	Oracle	SAP	MercuryGate
Functional Capabilities	Order Management	OM	✓	✓	✓
	Carrier Selection	CS	✓	✓	✓
	Route Optimization	RO	✓	✓	✓
	Freight Audit & Payment	FAP	✓	✓	✓
	Load Building	LB	✓	✓	✓
	Multimodal Support	MM	✓	✓	✓
	Spot/Contract Rate Handling	SR	✓	✓	✓
	Visibility & Tracking	VT	✓	✓	✓
Technical Features	Cloud Deployment	CD	✓	✓	✓
	API/EDI Integration	API	✓	✓	✓
	Customization Support	CSUP	✓	✓	✓
	Technical Scalability	TS	✓	✓	✓
	Platform UI/UX	UX	✓	✓	✓
Vendor & External Factors	Global Support	GS	✓	✓	✓
	Industry Adoption	IA	High	High	Medium
	Implementation Complexity	IC	High	Medium	Low
	Cost Structure	COST	High	Medium	Medium
	Sustainability Tools	SUST	Yes	Yes	Partial

Source: Authors' own research

The final step involves presenting the decision recommendation and performing sensitivity analysis. Stakeholders review the ranked TMS list, then adjust major criteria weights to test ranking stability. Consistent results indicate a stable decision; otherwise, comparisons or factor importance may be revised.

Priority Weights and Supermatrix Construction in TMS Evaluation

To demonstrate the ANP framework for TMS selection, consider two technical criteria: Technical Scalability (TS) and Cost Efficiency (COST). A logistics expert judges TS to be four times more important than Cost. This judgment forms the pairwise comparison matrix (Table 6) used to derive relative priority weights.

Table 6: Pairwise Comparison Matrix and Column Sums example

Criteria	TS	COST	Column Total ($\delta_{_j}$)
TS	1	4	5
COST	1/4	1	1.25

Source: Authors' own research

The matrix is then normalized by dividing each entry by the total of its respective column, resulting in the normalized matrix in Table 7. To compute the priority weights, the average of each row is calculated. The resulting weights represent the relative importance of each criterion in relation to the technical capability of TMS platforms (Table 8).

Table 7: Normalized Pairwise Comparison Matrix

Criteria	TS	COST
TS	0.8	0.8
COST	0.2	0.2

Source: Authors' own research

Table 8: Derived Priority Weights example

Criterion	Weight ($w_{_i}$)
TS	0.8
COST	0.2

Source: Authors' own research

After assigning priority weights, TMS options (e.g., Oracle TMS, SAP TM, MercuryGate) are evaluated per criterion. Carrier Portfolio Management (CPM), crucial for scalability and cost control, is assessed based on platform support and its dependencies on System Architecture (SA) and Freight Rate Flexibility (FRF) within the technical cluster, analyzed via pairwise comparison.

Table 9: Example of the Decision Matrix for the three TMS system

TMS Alternatives	Online dashboard	Configure settings and services	Shipment booking	Manifest	Label printing	Return label in the box
Oracle TM	4	5	3	5	5	2
SAP TM	3	1	4	5	4	5
MercuryGate	4	1	5	1	3	1

Source: Authors' own research

An unweighted supermatrix captures all direct relationships among criteria and alternatives, with a CPM segment in Appendix A. Inter-cluster comparisons among Technical Capabilities, Organizational Fit, and Strategic Environment use formulas from Appendix A. These form the dimension matrix, which weights the unweighted supermatrix to create the weighted supermatrix (Appendices B and C). Iterative multiplication produces the limit supermatrix, yielding stable priority values that rank TMS alternatives. Final scores across all criteria, shown in Appendix B, indicate the most suitable TMS for the organization.

Table 10 : Ranking of TMS systems

TMS Alternative	Total Score
MercuryGate	384
Oracle TM	374
SAP TM	350

Source: Authors' own research

According to the proposed TMS Selection Matrix , the optimal TMS system matching the fictional company profile in this example is MercuryGate with a total score of 384 points.

Conclusion

Transport Management Systems (TMS) are essential for logistics managers to oversee, coordinate, and optimize transport operations. However, selecting the right TMS is complex, involving diverse functional, technical, and strategic requirements. With varying organizational contexts and external factors like regulations and technology trends, TMS selection becomes a classic multi-criteria decision-making (MCDM) problem that requires a structured approach to ensure alignment with logistics operations and broader business goals. We analyzed studies on TMS integration and identified key challenges in the selection process. Additionally, we reviewed literature on software tool selection and adapted project management selection methodologies to incorporate internal and external variables influencing TMS adoption. The resulting framework offers a holistic and systematic perspective, clarifying the interconnections between factors that affect implementation success. This study also provides logistics companies with a practical framework for selecting TMS platforms, adaptable to various organizational profiles and systems. However, the study is limited by its reliance on literature, lacking empirical validation. Future research should apply and refine the framework in real-life settings. Another limitation is limited access to grey literature, as internal company documents are often unavailable. Potential sampling issues that may have excluded relevant studies should also be acknowledged.

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