



Evaluating the Driving Effects of Digital Transformation on Sustainable Food Supply Chains: A SCOR-TOPSIS Approach

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ABSTRACT

Digital transformation (DT) has emerged as a key driver of sustainable supply chain development. However, the role of DT in food supply chains (FSCs) has received limited attention. In particular, few studies have quantitatively examined how its driving effects vary across different supply chain processes from a process-oriented perspective. To address this gap, this study evaluates the driving effects of DT on the sustainable development of FSCs. Drawing on sustainable supply chain theory, an evaluation indicator system covering economic, environmental, and social dimensions is developed. The key processes of the FSCs are then identified based on the Supply Chain Operations Reference (SCOR) model and treated as the evaluation objects. Expert assessments are aggregated using the arithmetic mean, and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is applied to evaluate and rank the different supply chain processes. The results reveal clear differences in the driving effects of DT across the selected processes. Among them, the distribution process exhibits the strongest overall performance, followed by the storage and transportation process, while the procurement process performs relatively weakly. From a process-differentiated perspective, this study demonstrates how DT contributes to the sustainable development of FSCs through different operational processes. The findings provide a structured decision-making basis for identifying priority areas and formulating differentiated DT strategies to enhance FSCs sustainability.

1. Introduction

The food supply chains (FSCs) encompass multiple stages, including production, procurement, storage and transportation, and distribution, and serves as a critical link between food production and consumption. As the pursuit of high-quality development continues to deepen, the development of FSCs can no longer focus solely on the traditional objective of ensuring supply. Increasing attention has been placed on improving efficiency, reducing losses, conserving resources, promoting green development, and strengthening coordination and governance [1]. Against the backdrop of continued agricultural modernization, transforming FSCs from conventional operating models toward more efficient, environmentally sustainable, and coordinated systems has become a critical research and practical concern [2].

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Against this background, DT provides new opportunities to enhance the sustainability of FSCs [3]. The integration of digital technologies can improve information collection, analysis, and sharing, while facilitating coordination between production and distribution, inventory management, and logistics operations [4, 5]. It can also enhance end-to-end traceability and supply chain transparency, reduce resource waste and distribution losses, and support improvements in operational practices, resource allocation, and value creation. In recent years, the increasing convergence of digitalization and green development has accelerated the adoption of emerging technologies, such as artificial intelligence, the Internet of Things, and robotics, across agricultural production, storage, logistics, and distribution. Meanwhile, greater attention has been directed toward improving circulation efficiency, reducing food losses, and promoting low-carbon development [5]. DT is therefore becoming an increasingly important driver of operational efficiency, resource utilization, and sustainability in FSCs.

Existing studies have largely examined the application of digital technologies from the perspectives of digital agriculture, smart logistics, and food traceability [6, 7]. Although the relationship between DT and FSCs sustainability has received increasing attention, its driving effects have rarely been examined systematically from a supply chain process perspective [8]. In particular, comprehensive assessments of the magnitude and variation of these effects across different supply chain processes remain limited. Different processes within FSCs vary considerably in their functional roles, resource inputs, technological foundations, and sustainability objectives [9]. The effects of DT are therefore unlikely to be uniform across these processes. This highlights the need for a systematic evaluation framework to measure and compare its driving effects [10].

Accordingly, this study develops an evaluation indicator system for the driving effects of DT based on sustainable supply chain theory and the operational characteristics of FSCs [11]. The Supply Chain Operations Reference (SCOR) model is used to identify the key processes of the FSCs, which are treated as the evaluation objects [12]. Expert assessments are then aggregated using a weighted averaging method. TOPSIS is subsequently applied to measure and rank the driving effects across the different processes [13]. The analysis aims to reveal process-level differences in how DT contributes to FSCs sustainability. The findings provide decision support for prioritizing digital transformation initiatives in FSCs.

2. Literature review

This section reviews the literature relevant to the present study from two perspectives. First, it examines existing research on the relationship between DT and sustainability. Second, it summarizes the applications of TOPSIS in sustainability and supply chain evaluation. Based on these two research streams, the remaining gaps are identified to clarify the positioning of this study.

2.1 Literature review on the relationship between DT and sustainability

Against the backdrop of mounting global resource and environmental constraints, sustainable development has become a central objective of socioeconomic development. Meanwhile, rapid advances in next-generation information technologies, including big data, the Internet of Things, and artificial intelligence (AI), have made DT an increasingly important pathway toward sustainability [14; 15]. Existing studies suggest that DT can improve resource-use efficiency, facilitate industrial upgrading and restructuring, and reduce environmental burdens through the integration of digital technologies and innovation in business and operational models [16, 17]. These effects can contribute to the *coordinated pursuit of economic, environmental, and social objectives*.

From the perspective of research content, scholars have first examined the application pathways of DT across different fields. Pauliuk *et al.* [18], from a systems transition perspective, argued that

digital technologies can optimize patterns of resource utilization and thereby support the achievement of sustainable development goals. Xu *et al.* [19] provided empirical evidence *that* DT can significantly improve the efficiency of green technological innovation at the firm level. Jiang *et al.* [20] further investigated the urban context and *demonstrated* that digital development can contribute to the sustainable use of resources. In addition, Škare *et al.* [21] suggested that digitalization not only promotes economic growth *but also* exerts important effects on carbon emissions and environmental performance.

At the industry level, the integration of DT and sustainability exhibits clear sector-specific characteristics. Benavides-Espinosa *et al.* [22] found that, in the agri-food sector, DT can improve firm performance by strengthening innovation capabilities and enhancing operational efficiency. From a dynamic capabilities perspective, Cannas [23] argued that digital technologies can enhance firms' ability to respond to complex and changing external environments. Schilling and Seuring [24], focusing on the supply chain context, further identified digital practices as an important mechanism for advancing sustainable supply chain management. Meanwhile, Dal Mas *et al.* [25] systematically reviewed the development and application of DT in the sustainability field, indicating that a substantial body of research has already been established in this area.

From a methodological perspective, existing studies have generally followed two analytical approaches. The first consists of empirical studies based on econometric and statistical methods. These studies typically employ regression analysis, structural equation modeling, and related techniques to examine the mechanisms through which DT affects sustainable development. For example, Li [26] used confirmatory factor analysis to investigate the relationship between DT and economic sustainability performance. Guo *et al.* [27] employed a regression model to examine the effect of digital development on green innovation.

The second stream of research applies multi-criteria decision-making (MCDM) methods to evaluate the sustainability effects of DT. Dwivedi and Paul [28] used a fuzzy BWM approach to assess the contribution of digital supply chains to corporate sustainability performance. Rahimi *et al.* [29] adopted a fuzzy DNMA model to identify key barriers to DT. Bagherian *et al.* [30] further employed a DEMATEL-ISM framework to analyze *the mechanisms* through which digital technologies influence energy sustainability.

Overall, prior research has examined the contribution of DT to sustainable development from multiple perspectives, including the macroeconomic level, the firm level, and the supply chain level. A broad consensus is that DT can support sustainability by improving resource-use efficiency, promoting green innovation, and enhancing system operations. Nevertheless, several gaps remain. First, relatively limited attention has been paid to the FSCs as a complex and interconnected system. Second, most studies focus on causal mechanisms, while systematic assessments of the driving effects of DT remain insufficient. Third, existing methods rarely provide an integrated evaluation framework that captures multiple supply chain processes and multiple actors. These limitations highlight the need for a systematic approach to evaluate the driving effects of DT across FSCs.

2.2 Literature review on TOPSIS method

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has been widely applied to the evaluation and ranking of complex decision problems because of its simple structure, transparent computational procedure, and strong interpretability. The method constructs a positive ideal solution and a negative ideal solution, and then calculates the distance between each alternative and these two reference points. Alternatives are subsequently ranked according to their relative closeness to the ideal solution. TOPSIS can accommodate both quantitative and qualitative criteria, making it particularly suitable for resource allocation and system evaluation problems [31].

Related studies have shown that TOPSIS has become an important tool in multi-criteria decision-making and has been extensively applied in supply chain management, resource management, and engineering decision-making.

With the continued development of decision-making research, TOPSIS has gradually evolved from its classical form into a variety of extended models. To address the uncertainty commonly encountered in real-world decision environments, fuzzy set theory has been incorporated into TOPSIS, leading to fuzzy TOPSIS and its numerous variants. These extensions enhance the ability of the method to represent vague and imprecise information [32]. Rough set theory and its extended forms, such as Hyper Rough Sets and Super Hyper Rough Sets, have also been integrated into the TOPSIS framework. By constructing lower and upper approximations, these approaches improve the treatment of incomplete information and strengthen the adaptability of TOPSIS in complex decision environments. In addition, increasing attention has been paid to the integration of TOPSIS with Neutrosophic Sets, neural networks, and related techniques. Such hybrid approaches combine uncertainty modeling with machine-learning mechanisms and can improve both decision accuracy and computational efficiency in multi-attribute decision-making problems [33].

Regarding methodological improvements, the determination of criterion weights remains a key factor affecting TOPSIS results. Traditional approaches often rely heavily on subjective weighting and may therefore introduce bias into the evaluation process. To address this limitation, various objective weighting methods have been incorporated into TOPSIS, including the entropy weighting method and CRITIC [34-36]. These approaches derive criterion weights from the information contained in the decision matrix, such as data dispersion, contrast intensity, and inter-criterion correlations. They can therefore reduce reliance on subjective judgments and improve the objectivity of evaluations based on TOPSIS.

From an application perspective, TOPSIS has been widely employed across various fields and has increasingly been extended to sustainability and supply chain management. In the field of resource and environmental management, TOPSIS and fuzzy TOPSIS have been used to comprehensively evaluate water resource management alternatives, thereby providing decision support for sustainable resource allocation [37]. In environmental protection research, TOPSIS has also been applied to the measurement of agricultural carbon emissions and the assessment of low-carbon development. Such applications provide an important basis for promoting green agricultural development and formulating carbon reduction strategies. In manufacturing and supply chain management, TOPSIS has been extensively used for process optimization, supplier selection, and supply chain performance evaluation, contributing to improvements in operational efficiency and competitiveness [38, 39]. Comparative studies in fields such as software engineering have further shown that TOPSIS offers certain advantages in reducing decision complexity and mitigating rank reversal problems [32].

Despite its broad applicability, TOPSIS also has several limitations. First, the results are sensitive to criterion weights, and different weighting schemes may lead to different rankings. Second, conventional TOPSIS has limited ability to represent highly uncertain information and therefore often requires extensions under fuzzy or other uncertainty-based environments. In addition, the construction of ideal solutions and the choice of normalization methods may affect the final results. Accordingly, recent studies have increasingly focused on hybrid and intelligent extensions of TOPSIS. By integrating fuzzy theory, rough sets, and artificial intelligence techniques, these approaches seek to improve the robustness and adaptability of the method [33].

In the context of sustainable FSCs, TOPSIS provides an appropriate approach for integrating multidimensional criteria covering economic, environmental, and social aspects. It therefore offers methodological support for evaluating the driving effects of DT. Building on this rationale, the present

study incorporates the (SCOR) model into the TOPSIS framework to structure the operational processes of the FSCs and define the corresponding evaluation objects and criteria. On this basis, an integrated SCOR-TOPSIS evaluation framework is developed to systematically assess the driving effects of DT on sustainable FSCs.

3 Evaluation of DT effects in sustainable FSCs

Developing an appropriate evaluation system is essential for assessing the driving effects of DT and conducting subsequent TOPSIS analysis. As this study focuses on different processes of sustainable FSCs rather than a single firm or activity, the framework should reflect both process characteristics and multidimensional sustainability requirements. Accordingly, the SCOR model is used to define the evaluated processes, while sustainable supply chain theory guides the selection of evaluation criteria. This forms an integrated framework combining SCOR processes with sustainability indicators.

3.1 Identification of key processes

DT has clear process level heterogeneity in its effects on FSCs. Its influence is not evenly distributed across supply chain stages but is transmitted through different functional processes. Therefore, dividing the supply chain from a process perspective helps identify the specific carriers through which the driving effects of DT are realized.

SCOR model adopts a process-oriented perspective and divides the supply chain into several interconnected core processes. It provides a systematic representation of supply chain operations, ranging from resource allocation and product distribution to resource recovery and reuse. Compared with traditional linear classifications, the SCOR model covers not only forward processes such as planning, sourcing, production, and delivery, but also downstream and reverse processes including use, return, and regeneration. It therefore provides a more comprehensive representation of closed loop supply chain operations.

Each process performs a distinct function and together they constitute the basic operational structure of the supply chain. In the conventional SCOR framework, Plan focuses on coordinating supply and demand and supporting resource planning, while Source involves the procurement of required materials and services. Make covers material transformation and production activities, whereas Deliver involves order fulfillment, transportation, and distribution. Return addresses reverse flows, while Enable supports the overall management and coordination of supply chain activities [40]. In circular *supply chain* settings, the SCOR framework has been further extended to include Use and Recover. These processes capture product use, end of use activities, reverse flows, and resource recovery, thereby providing a more complete representation of closed loop supply chain operations [41]. For the evaluation objects, this study identifies four key processes based on the structural characteristics of the FSCs: production, sourcing, storage and transportation, and distribution, denoted as A_1 , A_2 , A_3 and A_4 respectively. These processes differ in their functions, resource inputs, information coordination, and operational efficiency. The mechanisms and effects of DT may therefore vary across them. Treating these key processes as evaluated processes enables a comparative assessment of the driving effects of DT across different supply chain stages.

3.2 Construction of the indicator system

After clarifying the research objective of evaluating the driving effects of DT, the development of an evaluation indicator system becomes a critical foundation for subsequent empirical analysis and TOPSIS ranking. Since this study does not focus on a single firm or a specific operational activity but rather examines the effects of DT across different processes of sustainable FSCs, the indicator system

should capture both the characteristics of the entire supply chain and the multidimensional aspects of sustainability. Accordingly, the SCOR model is introduced at the alternative level, while sustainable supply chain theory is incorporated at the criterion level to develop an integrated evaluation framework combining SCOR processes with sustainability indicators.

The SCOR model provides a systematic process-based approach for classifying supply chain activities. With strong structural consistency and broad applicability, it can effectively represent the operational logic of FSCs, from upstream planning to downstream resource recovery. Therefore, the five key processes identified above are selected as the evaluation objects for assessing the driving effects of DT. The evaluation focuses not only on comparisons among different entities, but also on identifying variations in the effects of DT across supply chain processes. This approach helps reveal critical driving processes and relatively weak areas.

Regarding evaluation criteria, the impacts of DT on FSCs are multidimensional. They are reflected not only in efficiency improvement and cost optimization, but also in resource utilization, environmental impact reduction, food safety assurance, and information coordination. Therefore, a single-dimensional evaluation approach cannot fully capture its comprehensive effects. Based on the sustainable supply chain perspective, this study develops an indicator system from three dimensions: economic, environmental, and social sustainability. The economic dimension focuses on operational efficiency and cost management, the environmental dimension evaluates resource utilization and environmental performance, and the social dimension emphasizes supply assurance, quality and safety, and information collaboration. Through the integration of these dimensions, the driving effects of DT on sustainable FSCs can be systematically evaluated.

The selection of specific indicators follows three principles: comprehensiveness, representativeness, and operability. Comprehensiveness ensures that the indicators cover the major processes of FSCs and correspond with the SCOR framework. Representativeness ensures that the indicators reflect the key characteristics through which DT promotes sustainability. Operability indicates that the indicators can be obtained through expert assessments, thereby supporting the evaluation process. Table 1 presents the detailed evaluation indicators, their definitions, and corresponding attribute types. These indicators provide a comprehensive basis for evaluating the digital transformation performance of different food supply chain processes.

The economic dimension is designed to reflect the role of DT in improving supply chain operational efficiency and optimizing cost structures. Specifically, demand responsiveness and inventory turnover rate represent the effectiveness of demand forecasting and resource allocation. Production efficiency reflects the level of production organization and scheduling. Procurement cost control level, logistics cost level, and order fulfillment capability further capture supply chain performance in procurement coordination, logistics operations, and order execution.

The environmental dimension focuses on the influence of DT on the green development capacity of FSCs. It mainly considers two aspects: improving resource utilization efficiency and reducing environmental burdens. Energy utilization efficiency and water resource utilization rate indicate the level of resource conservation. Carbon emission intensity reflects environmental impacts, while food loss rate measures the capability of controlling losses during storage, transportation, and distribution.

The social dimension represents the role of FSCs in ensuring public welfare and enhancing collaborative governance. Information transparency reflects the level of information sharing and traceability within the supply chain, which contributes to improving operational reliability and coordination. Digital capability level captures the ability of organizations and personnel to apply digital technologies and serves as an important foundation for efficient supply chain operations.

Table 1

Evaluation indicator system

Dimension	SCOR Process	Indicator	Indicator Description	Type
Economic	Plan	Demand Responsiveness (X_1)	Ability to respond to market changes	Benefit
	Plan	Inventory Turnover Rate (X_2)	Efficiency of inventory resource allocation	Benefit
	Source	Procurement Cost Control Level (X_3)	Ability to optimize procurement costs	Cost
	Make	Production Efficiency (X_4)	Output level per unit of time	Benefit
	Deliver	Order Fulfillment Capability (X_5)	Ability to complete orders on schedule	Benefit
	Deliver	Logistics Cost Level (X_6)	Logistics cost per unit output	Cost
Environmental	Make	Energy Utilization Efficiency (X_7)	Energy consumption per unit output	Benefit
	Make	Water Resource Utilization Rate (X_8)	Efficiency of agricultural water resource utilization	Benefit
	Make	Carbon Emission Intensity (X_9)	Degree of environmental impact	Cost
Social	Deliver	Food Loss Rate (X_{10})	Degree of losses during storage and transportation	Cost
	Source	Information Transparency (X_{11})	Level of traceability and information sharing	Benefit
	Enable	Digital Capability Level (X_{12})	Personnel skills and organizational adaptability	Benefit

To improve the consistency between evaluated processes and criteria, this study further integrates the indicator system into the process structure of the SCOR model. Specifically, the Plan process emphasizes demand forecasting and resource coordination, corresponding to indicators such as demand responsiveness and inventory turnover rate. The Source process involves resource acquisition and supply coordination, which is associated with procurement cost control level. The Make process focuses on production organization and resource inputs, corresponding to production efficiency, energy utilization efficiency, water resource utilization rate, and carbon emission intensity. The Deliver process reflects logistics distribution and order fulfillment, corresponding to logistics cost level, fulfillment capability, and food loss rate. The Enable process supports the entire supply chain and is related to fundamental indicators such as information transparency and digital capability level.

Regarding data collection, the values of all indicators are obtained through expert assessments. 1-10 scoring scale is adopted to evaluate the performance of each alternative under different criteria. Assuming equal weights among experts, the arithmetic mean method is applied to aggregate individual evaluations and construct the decision matrix. This approach maintains computational simplicity while reducing the potential bias caused by subjective weighting schemes.

Overall, the proposed evaluation framework identifies the key FSCs processes based on the SCOR model and develops a multidimensional indicator system guided by sustainable supply chain theory. The framework evaluates the contribution of DT across economic, environmental, and social dimensions and provides the basis for subsequent quantitative assessment using the TOPSIS method.

4 TOPSIS-based evaluation frameworks for key processes in FSCs

Based on the evaluation framework developed in the previous section, this section further conducts a quantitative assessment of the digital transformation performance across key FSCs

processes using the TOPSIS method. The evaluation results are obtained through expert data collection, TOPSIS-based calculation, and comparative analysis of different processes. The following subsections describe the evaluation procedure and discuss the ranking results. The overall evaluation framework is illustrated in Figure 1.

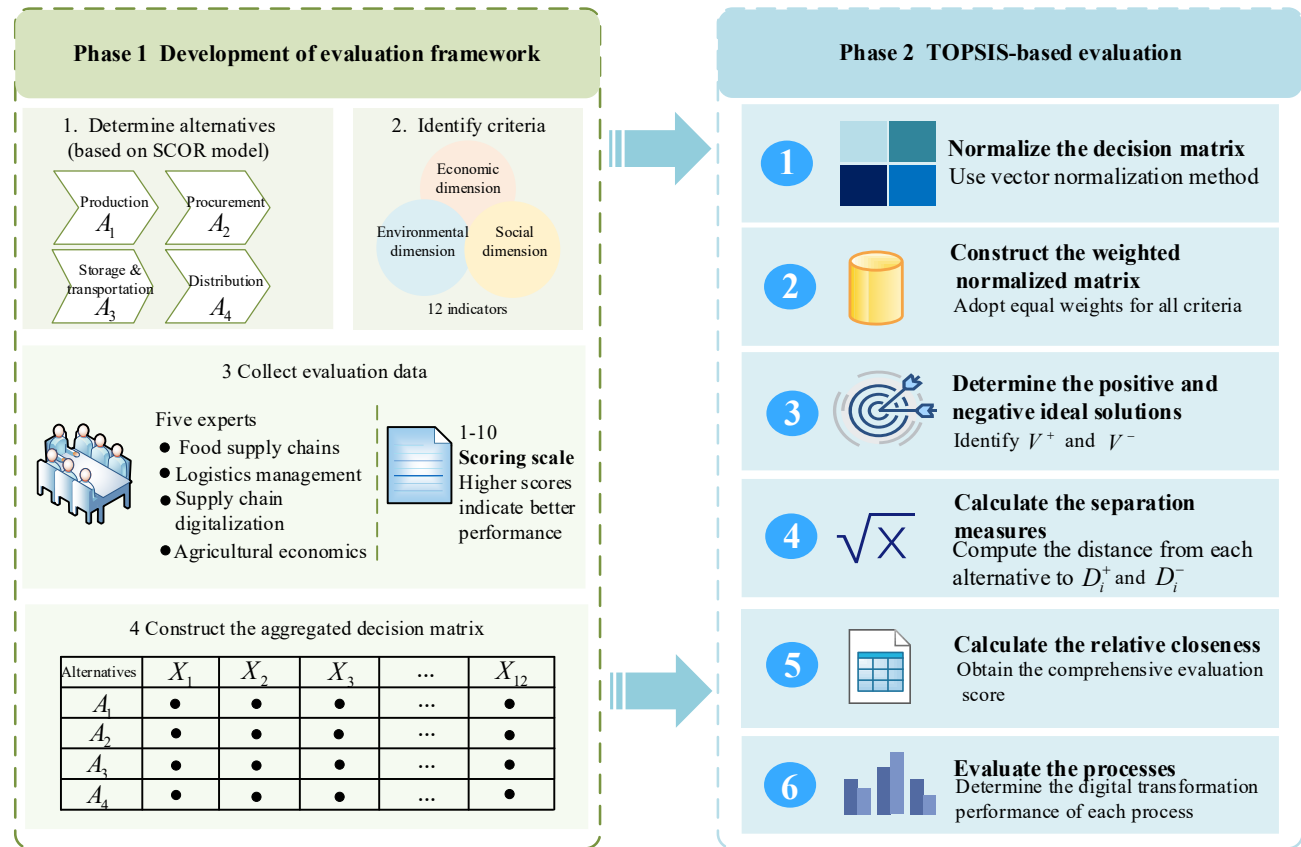


Fig. 1. Framework for evaluating the driving performance of DT across key FSC processes

4.1 Data collection for evaluation

Considering that the DT performance of key FSCs processes cannot be fully captured through standardized statistical data, this study adopts an expert scoring approach to obtain the original evaluation data. Five experts with relevant knowledge and professional experience in FSCs, logistics management, supply chain digitalization, and agricultural economics were invited to evaluate the performance of four key processes across 12 criteria. $A_1 - A_{10}$ scoring scale was adopted, where higher scores indicate better performance of the corresponding alternative under the given criterion. Assume that x_{ij}^k represents the evaluation score given by expert k for alternative i with respect to criterion j . The evaluation results from the five experts are presented as follows. The individual evaluation matrices of experts $E_1 - E_5$ are presented in Tables 2, 3, 4, 5 and 6, respectively.

4.2 Construct the aggregated decision matrix

Since the five experts are assigned equal weights, the arithmetic mean is used to aggregate their evaluation scores. Let x_{ij} denote the aggregated score of key processes i with respect to criterion j . It is calculated as follows:

$$x_{ij} = \frac{1}{5} \sum_{k=1}^5 x_{ij}^k \quad (1)$$

where x_{ij} represents the aggregated original evaluation value, and x_{ij}^k denotes the original score provided by expert k . Accordingly, the aggregated decision matrix $X = (x_{ij})_{4 \times 12}$ is obtained, as presented in Table 7.

Table 2

Evaluation matrix of expert

Alternative	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
A_1	6	6	6	9	7	6	9	9	6	7	6	6
A_2	7	7	8	6	7	7	6	6	7	7	7	6
A_3	8	8	7	7	9	9	7	7	7	9	7	7
A_4	9	9	7	7	9	8	7	7	7	9	9	9

Table 3

Evaluation matrix of expert

Alternative	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
A_1	6	6	7	9	7	6	8	9	6	6	6	6
A_2	7	7	8	6	7	7	6	6	7	7	6	6
A_3	8	8	7	7	9	9	7	7	7	9	7	7
A_4	9	9	7	7	9	8	7	7	7	9	9	9

Table 4

Evaluation matrix of expert

Alternative	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
A_1	6	6	6	8	7	6	9	8	6	7	6	6
A_2	7	7	8	6	7	7	6	6	7	7	7	6
A_3	8	8	7	7	9	8	7	7	7	9	7	7
A_4	9	9	7	7	9	8	7	7	7	9	9	9

Table 5

Evaluation matrix of expert

Alternative	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
A_1	6	6	6	9	7	6	9	9	6	7	6	6
A_2	7	7	7	6	7	7	6	6	7	7	7	6
A_3	8	8	7	7	9	9	7	7	7	9	7	7
A_4	9	9	7	7	9	8	7	7	7	9	9	9

Table 6

Evaluation matrix of expert

Alternative	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
A_1	6	6	6	9	7	6	9	9	6	7	6	6
A_2	7	7	8	6	7	7	6	6	7	7	7	6
A_3	8	8	7	7	9	9	7	7	7	9	7	7
A_4	9	9	7	7	9	8	7	7	7	9	9	9

Table 7

Aggregated decision matrix

Alternative	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
A_1	6.0	6.0	6.2	8.8	7.0	6.0	8.8	8.8	6.0	7.0	6.0	6.0
A_2	7.0	7.0	7.8	6.0	7.0	7.0	6.0	6.0	7.0	7.0	7.0	6.0
A_3	8.0	8.0	7.0	7.0	9.0	8.0	7.0	7.0	7.0	9.0	7.0	7.0
A_4	9.0	9.0	7.0	7.0	9.0	8.0	7.0	7.0	7.0	9.0	9.0	9.0

4.3 Normalize the decision matrix

Because the criteria differ in their measurement units and value ranges, the aggregated decision matrix needs to be normalized. This study adopts the vector normalization method. Let $Z = (z_{ij})_{4 \times 12}$ denote the normalized decision matrix, where z_{ij} represents the normalized value of alternative i with respect to criterion j . It is calculated as follows:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^4 x_{ij}^2}} \quad (2)$$

The resulting normalized decision matrix is presented in Table 8.

Table 8

Normalized decision matrix

Alternative	X_1	X_2	X_3	...	X_7	...	X_{11}	X_{12}
A_1	0.396	0.396	0.459	...	0.647	...	0.396	0.396
A_2	0.462	0.462	0.577	...	0.441	...	0.462	0.396
A_3	0.528	0.528	0.518	...	0.515	...	0.462	0.462
A_4	0.593	0.593	0.518	...	0.515	...	0.593	0.593

4.4 Construct the normalized matrix

In the evaluation indicator system developed in this study, all criteria jointly reflect the overall performance of key FSCs processes under DT. To reduce potential bias arising from subjective weighting and to maintain computational simplicity, equal weights are assigned to all criteria. Specifically:

$$w_j = \frac{1}{12}, j = 1, 2, \dots, 12 \quad (3)$$

where w_j denotes the weight assigned to criterion j .

On this basis, the weighted normalized matrix $V = (v_{ij})_{4 \times 12}$ is constructed, where v_{ij} represents the weighted normalized value of alternative i with respect to criterion j . It is calculated as follows:

$$v_{ij} = w_j z_{ij} \quad (4)$$

Accordingly, the weighted normalized matrix is obtained, as presented in Table 9.

Table 9

Weighted normalized decision matrix

Alternative	X_1	X_2	X_3	...	X_7	...	X_{11}	X_{12}
A_1	0.0330	0.0330	0.0383	...	0.0539	...	0.0330	0.0330
A_2	0.0385	0.0385	0.0481	...	0.0368	...	0.0385	0.0330
A_3	0.0440	0.0440	0.0432	...	0.0429	...	0.0385	0.0385
A_4	0.0494	0.0494	0.0432	...	0.0429	...	0.0494	0.0494

4.5 Determine the positive and negative ideal solutions

TOPSIS ranks the evaluated processes by comparing their relative proximity to the positive ideal solution and the negative ideal solution. Let the positive ideal solution be denoted by V^+ and the negative ideal solution by V^- . They are defined as follows:

$$V^+ = \{v_1^+, v_2^+, \dots, v_{12}^+\} \quad (5)$$

$$V^- = \{v_1^-, v_2^-, \dots, v_{12}^-\} \quad (6)$$

For benefit criteria, the positive and negative ideal values are determined as follows:

$$v_j^+ = \max_i(v_{ij}), v_j^- = \min_i(v_{ij}), \quad (7)$$

For cost criteria, the positive and negative ideal values are determined as follows:

$$v_j^+ = \min_i(v_{ij}), v_j^- = \max_i(v_{ij}), \quad (8)$$

Accordingly, the positive and negative ideal solutions are obtained, as presented in Table 10.

Table 10

Positive and negative ideal solutions

Indicator	Type	V^+	V^-
X_1	Benefit	0.0494	0.0330
X_2	Benefit	0.0494	0.0330
X_3	Cost	0.0383	0.0481
X_4	Benefit	0.0539	0.0368
X_5	Benefit	0.0465	0.0362
X_6	Cost	0.0328	0.0481
X_7	Benefit	0.0539	0.0368
X_8	Benefit	0.0539	0.0368
X_9	Cost	0.0378	0.0442
X_{10}	Cost	0.0365	0.0469
X_{11}	Benefit	0.0494	0.0330
X_{12}	Benefit	0.0494	0.0330

4.6 Calculate the separation measures

Let D_i^+ denote the distance between alternative i and the positive ideal solution, and D_i^- denote the distance between alternative i and the negative ideal solution. Both distances are calculated using the Euclidean distance. The corresponding formulas are given as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{12} (v_{ij} - v_j^+)^2} \quad (9)$$

$$D_i^- = \sqrt{\sum_{j=1}^{12} (v_{ij} - v_j^-)^2} \quad (10)$$

where D_i^+ represents the distance between alternative i and the positive ideal solution, while D_i^- represents the distance between alternative i and the negative ideal solution. The calculated distances are presented in Table 11.

4.7 Calculate the relative closeness and ranking outcomes

Let C_i denote the relative closeness of alternative i . It is calculated as follows:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, i = 1, 2, 3, 4 \quad (11)$$

where $0 \leq C_i \leq 1$. A larger C_i indicates that the alternative is closer to the positive ideal solution and therefore has better overall performance. Accordingly, the relative closeness values and ranking results of all processes are presented in Table 12.

Table 11

Distances of each alternative from the positive and negative ideal solutions

Alternative	D_i^+	D_i^-
A_1	0.0312	0.0294
A_2	0.0310	0.0188
A_3	0.0221	0.0252
A_4	0.0191	0.0316

Table 12

Relative closeness and ranking results

Key processes	D_i^+	D_i^-	C_i	Rank
A_1	0.0312	0.0294	0.4851	3
A_2	0.0310	0.0188	0.3775	4
A_3	0.0221	0.0252	0.5328	2
A_4	0.0191	0.0316	0.6233	1

Based on the evaluation scores provided by the five experts, an aggregated decision matrix is constructed for the four key FSCs processes. TOPSIS is then applied to normalize the data, construct the weighted normalized matrix, determine the positive and negative ideal solutions, and calculate the relative closeness values. The results show clear differences in the overall performance of the four processes under DT. These findings provide a quantitative basis for further analyzing the driving effects of DT across FSCs processes.

4.8 Results analysis

According to the results in Table 12, the relative closeness values of the four key processes are ranked as follows: distribution process A_4 (0.6233), storage and transportation process A_3 (0.5328), production process A_1 (0.4851), and procurement process A_2 (0.3775). The results indicate clear differences in the driving effects of DT across supply chain processes. The distribution process performs best, followed by storage and transportation. The production process ranks third, while the procurement process shows the weakest performance.

(1) The distribution process shows the strongest driving effect.

The distribution process has the highest relative closeness and is therefore closest to the ideal solution. It performs particularly well in demand responsiveness, inventory turnover, order fulfillment, information transparency, and digitalization capability. As this process is directly connected to market demand, digital technologies can more effectively improve order processing, delivery coordination, and information sharing. Digital platforms, logistics tracking systems, and order management systems further enhance operational visibility and coordination. The distribution process also performs well in both economic and social dimensions. Improved delivery efficiency can reduce transaction and time costs, while greater transparency and traceability strengthen

coordination among supply chain participants. These results indicate that the distribution process is a key node where the driving effects of DT are most evident.

(2) The storage and transportation process shows strong advantages in loss control and fulfillment assurance.

The storage and transportation process ranks second, indicating strong overall performance in the DT of FSCs. It performs particularly well in order fulfillment, logistics cost control, and food loss reduction. Digital technologies can improve warehousing efficiency, transportation coordination, and inventory management, while also helping to reduce losses and enhance supply stability. The application of intelligent warehouse systems, environmental monitoring, route optimization, and inventory warning mechanisms further supports these improvements. However, information transparency and cross process coordination remain weaker than in the distribution process, which partly explains its lower overall ranking.

(3) The production process shows high resource efficiency but limited coordination.

The production process performs well in production efficiency, energy efficiency, and water resource utilization, indicating that digital technologies have improved production organization, process monitoring, and resource use. Applications such as precision agriculture, intelligent equipment, and data collection further support resource conservation and productivity gains. However, its performance in demand responsiveness, information transparency, and digitalization capability remains relatively moderate. This suggests that DT in production is still focused mainly on internal efficiency improvements, while coordination with procurement, storage and transportation, and distribution remains insufficient. Stronger cross process integration is therefore needed to fully realize the driving role of the production process.

(4) The procurement process shows relatively weak overall performance.

The procurement process ranks last, indicating a relatively large gap from the ideal solution. Although it performs reasonably well in procurement cost control, its performance in order fulfillment, information transparency, and digital support remains limited. This may be related to fragmented digital practices and insufficient information exchange with upstream and downstream partners. Procurement is also more vulnerable to information asymmetry, supply and demand fluctuations, and dispersed suppliers. Without integrated data platforms and effective information sharing mechanisms, its contribution to supply chain coordination remains constrained. These results suggest that procurement is a relatively weak link in the DT of FSCs and should be a key focus for future improvement.

(5) Differences across key processes in the three sustainability dimensions.

The evaluation results reveal clear differences across the economic, environmental, and social dimensions. Economically, the distribution and storage and transportation processes perform relatively well, particularly in demand responsiveness, order fulfillment, and logistics cost control. Environmentally, production shows stronger performance in energy and water resource utilization, while storage and transportation perform well in food loss control. Socially, distribution has the strongest advantage in information transparency and digitalization capability. Overall, production is more closely associated with resource efficiency, storage and transportation with loss control and fulfillment assurance, and distribution with information coordination and overall efficiency. Procurement shows greater room for improvement across all three dimensions.

(6) Mechanism Analysis of the Driving Effects of DT.

The results indicate that the effects of DT are unevenly distributed across FSCs processes, showing clear process level heterogeneity. This variation can be explained from three main perspectives.

First, different processes perform different functions, which shapes how digital technologies generate value. Distribution and storage and transportation are closely related to order fulfillment,

logistics coordination, and loss control. Digital investment in these processes can therefore be translated more directly into performance improvements. By contrast, production and procurement are more constrained by natural conditions, fragmented actors, and weaker information foundations.

Second, the degree of information dependence varies across processes. Processes with greater information transparency and stronger sharing mechanisms are more likely to benefit from digital coordination. The strong performance of distribution is closely related to its high dependence on information systems and platform based on collaboration.

Third, digital foundations differ across processes. Storage and transportation and distribution generally have higher levels of standardization, which facilitates the adoption of digital technologies. Production and procurement often face greater difficulties in data collection and coordination among dispersed participants, limiting the effects of DT.

Overall, the driving effects of DT on FSCs are clearly heterogeneous. Different processes therefore require differentiated DT strategies rather than a uniform approach.

5. Implications for DT in FSCs

Based on the evaluation results and mechanism analysis, this section further discusses the practical implications for enhancing DT in FSCs. The results indicate that the driving effects of DT vary across different supply chain processes. Therefore, improvement strategies should consider process-specific characteristics rather than adopting a uniform approach.

5.1 Prioritize digital upgrading in distribution and storage and transportation

Given their strong performance in the overall evaluation, distribution and storage and transportation should be regarded as priority areas for DT in FSCs. Digital investment in these processes can be translated relatively quickly into efficiency gains and loss reduction. In the distribution process, order management systems, intelligent delivery systems, and supply chain coordination platforms should be further developed to improve demand responsiveness and order fulfillment. In storage and transportation, greater attention should be given to intelligent warehousing, route optimization, and grain condition monitoring to reduce food losses and enhance logistics efficiency.

5.2 Strengthen coordination between production and other supply chain processes

Although the production process performs relatively well in resource utilization, its coordination with procurement, storage and transportation, and distribution still needs improvement. Greater integration should therefore be promoted through shared information platforms and data sharing mechanisms. In practice, agricultural production data platforms, order driven production, and stronger alignment between production planning and market demand can help shift DT from isolated optimization toward system wide coordination.

5.3 Strengthen digitalization in procurement to address supply chain weaknesses

Given the relatively low level of digitalization in procurement, greater attention should be paid to supply information integration and procurement coordination. A unified procurement information platform can improve the transparency of supply and demand information, while digitalized and standardized procurement processes can enhance efficiency and cost control. In addition, better integration and management of data from dispersed suppliers can help reduce the adverse effects of information asymmetry.

5.4 Promote digital coordination across the entire supply chain

DT in FSCs should extend beyond individual processes and promote information sharing and coordinated optimization across the entire chain. Integrated data platforms and information systems

can strengthen connectivity among planning, procurement, production, storage and transportation, and distribution, thereby improving overall operational efficiency. Particular attention should be given to data standardization, system compatibility, and cross organizational coordination to reduce information silos.

5.5 Adopt differentiated strategies to improve DT outcomes

Different supply chain processes vary in their functional roles, resource conditions, and digital foundations. DT should therefore be advanced through differentiated strategies. For distribution and storage and transportation, where digital capabilities are relatively strong, the application of advanced digital technologies can be further deepened. For production and procurement, greater priority should be given to strengthening digital infrastructure and information systems. A phased and targeted approach can support the gradual shift from local optimization to supply chain wide improvement.

6 Conclusions and future research

This section summarizes the main findings of the study and outlines directions for future research. Section 6.1 presents the principal conclusions regarding the driving effects of DT across key FSCs processes. Section 6.2 discusses the main limitations of the current study and proposes several directions for further research, particularly in terms of indicator development, data sources, and evaluation methods.

6.1 Research conclusions

First, based on a systematic review of studies on FSCs and DT, this study integrates the SCOR model with sustainable supply chain theory to develop an evaluation indicator system covering economic, environmental, and social dimensions. The analysis shows that FSCs play a critical role in linking production and consumption, and their operational efficiency and stability are closely related to food security. DT has increasingly become an important means of improving supply chain performance.

Second, four key processes-production, procurement, storage and transportation, and distribution-are selected as the evaluation objects. Their DT performance is assessed using 12 criteria. A decision matrix is constructed, and TOPSIS is applied to rank the four processes. The results reveal marked differences across supply chain processes. Distribution performs best, followed by storage and transportation, production, and procurement. This indicates that the driving effects of DT are unevenly distributed across the supply chain.

Third, the four processes show different strengths across the economic, environmental, and social dimensions. Distribution performs well in demand responsiveness, order fulfillment, and information transparency, highlighting the role of digital technologies in market connectivity and information coordination. Storage and transportation show advantages in logistics cost control and food loss reduction. Production performs relatively well in energy and water resource utilization, but cross process coordination remains limited. Procurement performs relatively weakly in information sharing and coordination, making it a key area for improvement.

Finally, the results indicate that DT contributes to FSCs mainly by improving operational efficiency, optimizing resource allocation, reducing losses, and strengthening information coordination. However, the pathways and effects vary across processes. DT strategies should therefore be differentiated according to process specific conditions. Priority should be given to key processes, while stronger coordination across the entire supply chain should be promoted to improve overall stability and sustainability.

6.2 Future research

Although this study provides a systematic assessment of the driving effects of DT on FSCs, several limitations remain.

First, the evaluation indicator system is mainly developed through literature review and theoretical analysis. Although the selected indicators are representative, some potentially important factors may not be fully captured. For example, climate change, market demand fluctuations, and policy interventions may also affect FSCs performance. Future studies could therefore expand the indicator system to improve the comprehensiveness of the evaluation.

Second, the original decision matrix is constructed using expert assessments. Although this approach can reflect overall evaluation tendencies, it inevitably involves a certain degree of subjectivity. The limited number of experts may also affect the robustness of the results. Future research could incorporate statistical data, firm level data, or case-based evidence to improve the objectivity and reliability of the evaluation.

Third, this study applies TOPSIS because of its computational simplicity and clear ranking logic. However, equal weights are assigned to all criteria, which may not fully reflect differences in criterion importance. Future studies could introduce entropy weighting, AHP, or combined weighting methods to obtain more differentiated criterion weights and improve evaluation accuracy.

Overall, future research can further extend the range of influencing factors, enrich data sources, and refine the evaluation methods. These improvements would provide a more comprehensive understanding of how DT affects FSCs and offers stronger theoretical and practical support for enhancing supply chain stability and sustainability.

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Conflicts of Interest

The authors declare no conflicts of interest.

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