Digital Supply Chain Practices and Firm Performance: The Mediating Role of Data-Driven Decision Making

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ABSTRACT

With the rapid advancement of digital technologies, Digital Supply Chains (DSC) have become critical to enhancing organizational productivity. The existing literature lacks integrated models that clearly explain the relationships among DSC practices, Data-Driven Decision-Making (DDDM), and Organizational Performance (OP). This study examines the effect of DSC practices on OP, with particular emphasis on the mediating role of DDDM. Drawing on the Resource-Based View (RBV), Dynamic Capabilities Theory, and Information Processing Theory, the study employs an online survey of 366 employees in Egypt's food and beverage supply chain sector. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.1. The findings indicate that DSC practices have a positive and significant effect on DDDM, which in turn substantially enhances firm performance. Moreover, DDDM serves as a mediating mechanism between DSC practices and OP, suggesting that the performance benefits of DSC resources are realized primarily through improved organizational decision-making processes.

Keywords-digital supply chain; data-driven decision-making; organizational performance

I. INTRODUCTION

The digital transformation of supply chain management is important in determining an organization's competitiveness and overall performance. The adoption of DSC practices, incorporating technologies such as cloud computing, blockchain, Artificial Intelligence (AI), and the Internet of Things (IoT), has significantly redefined supply chain operations by enhancing real-time visibility, automation, and process optimization [1]. By equipping businesses to proactively handle disruptions, optimize processes, and enhance overall responsiveness to market demands, these advancements improve supply chain resilience and efficiency [2, 3]. The successful implementation of DSC relies on integrating DDDM, which in turn leverages data analytics and predictive insights for strategic, tactical, and operational decision-making. Authors in [4] demonstrated that DDDM enhances decision accuracy, promotes agility, and enables organizations to address complex supply chain challenges effectively. By incorporating DDDM into supply chain operations, businesses can transition from a reactive to a proactive decision-making approach, including demand forecasting, real-time inventory management, and predictive maintenance [5]. Despite the growing popularity of DDDM and DSC practices for enhancing OP, current frameworks and models often fail to fully capture the interaction between these dimensions [4, 6]. Additionally, existing research primarily views DSC as a technological or operational competence, putting an emphasis on testing its direct relationship with corporate performance. While these studies prove that digitalization is important, they often regard digital technologies as self-contained performance drivers and pay insufficient attention to the organizational decision-making processes through which digital resources are translated into value [7, 8]. This limitation is especially pronounced in contexts characterized by institutional voids, uneven levels of digital maturity, and weak data governance, conditions that are prevalent in many emerging economies [9]. In such environments, firms may adopt DSC technologies without developing the complementary organizational capabilities needed to effectively manage and exploit data, thereby constraining the performance benefits of digital investments [10]. These challenges are particularly acute in the food and beverage industry, which is marked by demand volatility, product perishability, and strict quality requirements. Together, these characteristics intensify information-processing demands and necessitate timely, data-informed decision-making to sustain operational efficiency and performance [11, 12].

Furthermore, variation in organizations' digital and analytical capacities affects their ability to integrate analytics into managerial decision-making processes and extract value from digital resources [8]. Consequently, the effectiveness of DSC practices is significant to the development of DDDM capabilities, which support the systematic use of data in managerial decisions and have been associated with enhanced OP [7, 13]. Against this backdrop, there is a need for a more theoretically grounded explanation that goes beyond considering digitalization as a solely technical capability. This study, based on the Resource-Based View (RBV) and Dynamic Capabilities Theory, aims to clarify how DSC practices form strategic digital resources and how their value is realized through organizational decision-making processes in the Egyptian food and beverage industry. As a result, this study addresses the following research questions:

- RQ1: How may DSC practices be viewed as a bundle of strategic digital resources under the Resource-Based View (RBV)?
- RQ2: How can DDDM work as a dynamic capability, orchestrating DSC resources to improve business performance?

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

A. *DSC Practices, Strategic Resources, and Information - Processing Demand*

Drawing on the Resource-Based View (RBV), organizations gain long-term performance advantages when they have and effectively utilize Valuable, Rare, imperfectly Imitable, and Non-substitutable resources (VRIN) [14]. From this perspective, DSC practices can be conceptualized as a bundle of strategic digital resources, including IT infrastructure that enables real-time data capture and connectivity across supply chain partners, analytics capability that supports data processing and insight generation, and data governance routines that ensure data quality, accessibility, and appropriate use. Collectively, these resources exhibit the core VRIN attributes. They are valuable in enhancing supply chain visibility and responsiveness; rare because of firm-specific configurations of digital infrastructure, analytical expertise, and governance routines; difficult to imitate due to path dependency and the accumulation of tacit knowledge; and non-substitutable, as their combined effects cannot be easily replicated through alternative resources [8, 15]. However, consistent with Information Processing Theory, the performance value of these digital resources depends on their ability to effectively address the increased information-processing demands created by environmental uncertainty in contemporary supply chains [12]. While DSC practices improve organizations' ability to generate and access massive amounts of real-time data, they do not automatically solve information-processing issues. Digital data may stay underutilized or overrun managerial attention if proper organizational decision-making mechanisms are not in place, especially in situations with uneven digital maturity and insufficient data governance [10].

B. *The Effect of DSC Practices on DDDM*

The digitalization of supply chains has transformed modern organizational operations, facilitating the adoption of DDDM as a critical driver of both strategic and operational success [16]. It has been confirmed that digital tools enhance decision-making accuracy, efficiency, and reliability [17]. By enabling real-time data generation, processing, and utilization, these technologies strengthen DDDM capabilities across supply chain activities [18]. Authors in [2, 19] further emphasized that the integration of digital systems improves the quality and reliability of DDDM by ensuring that managerial decisions are based on timely, actionable insights rather than intuition or subjective judgment. In addition, data-driven strategies promote stronger alignment between operational and strategic objectives [6]. Cloud-based supply chain management systems and other collaborative digital technologies also support real-time data sharing, thereby enhancing collective and cross-functional decision-making [20]. Despite these advances, limited empirical research explains how digital supply chain activities enhance DDDM across different organizational contexts and industries [21]. Accordingly, this study examines the direct impact of DSC practices on DDDM to better understand how digital supply chain initiatives contribute to improved decision-making processes and, ultimately, superior performance outcomes. Therefore, the following hypothesis is proposed:

- H1: DSC practices positively influence DDDM

C. *DDDM as a Fit Mechanism*

Using Dynamic Capabilities Theory, this study conceptualizes DDDM as a higher-order decision-making capability that allows organizations to sense developing conditions, assess digitally generated supply chain data, and act through prompt and informed managerial reactions [22]. It has been shown that incorporating analytical insights into decision-making processes enhances decision quality and organizational outcomes [7, 13]. Within this framework, DDDM serves as a fit mechanism to match the information-processing capacity made possible by DSC practices with the growing information-processing demands. Instead of assuming direct technology effects, DDDM explains how DSC resources are transformed into firm performance by coordinating digital infrastructure, analytics capabilities, and governance routines into coherent managerial actions.

D. *The Effect of DDDM on OP*

Empirical evidence demonstrates a positive relationship between DDDM and OP. For example, authors in [23] reported that data-driven organizations achieve approximately 4%

higher productivity and 6% greater revenue compared to firms that rely primarily on intuition-based decision-making. Similarly, the findings in [24] indicated that DDDM enhances customer satisfaction, financial performance, and operational efficiency across a wide range of industries. To sustain competitive advantage in increasingly dynamic markets, organizations that adopt DDDM are also more inclined to explore innovative business models and develop novel products and services [25]. Moreover, digitalization is reshaping how organizations make decisions and conduct business, emphasizing agility and adaptability as important capabilities for long-term success [26]. Changes in customer behavior and market structures driven by digital technologies further contribute to improvements in supply chain and operational efficiency, with the potential to significantly transform overall business operations [27]. In addition, organizations that embed DDDM within supply chain processes tend to exhibit greater agility and resilience, particularly in the face of disruptions [4]. By leveraging data from sensors, Enterprise Resource Planning (ERP) systems, and customer interactions, firms can rapidly identify bottlenecks and operational inefficiencies. This data-driven approach supports continuous improvement initiatives, such as Lean and Six Sigma, enabling organizations to sustain high levels of operational excellence [24]. Collectively, these findings underscore the transformational role of DDDM in driving OP. On the contrary, several gaps exist in the literature on the connection between DDDM and OP; a lack of industry-specific insights is one of these, since previous research frequently extrapolates results from one area to another without taking sector-specific issues into account [27]. Additionally, there is an absence of uniform performance measures to account for the various DDDM outcomes [28]. To fill some of these gaps, the second hypothesis of this study is to investigate the impact of DDDM on OP within the food and beverage industry in Egypt as follows:

- H2: DDDM positively influences OP.

E. OP

OP encompasses financial and non-financial outcomes, including profitability, market share, operational efficiency, and customer satisfaction. Empirical studies link the use of DSC practices to improved performance metrics; organizations that use digital technologies in their supply chains, for example, report 15% higher customer satisfaction and 20% higher operational efficiency [25]. Authors in [23] found that organizations adopting DDDM are 5% more productive than those relying solely on intuition.

F. The Effect of DSC Practices on OP

Empirical research suggests that DSC practices significantly enhance both financial and operational OP. For instance, authors in [4] demonstrated that the adoption of DSC technologies improves manufacturing firms' financial outcomes and operational effectiveness. Similarly, authors in [29] conceptualized the DSC as a dynamic, intelligent value chain capable of rapid response and continuous adaptation. The integration of advanced digital technologies and analytics is a significant source of revenue growth, cost reduction, and profitability. Moreover, DSC practices enable manufacturers to better understand and anticipate customer behavior, allowing them to differentiate themselves within complex networks of suppliers, partners, and customers [30, 31]. Empirical evidence further shows that organizations applying big data analytics in their supply chains experience higher levels of customer satisfaction, profitability, and operational efficiency [6]. These findings underscore the transformative potential of DSC practices across multiple industries. By leveraging real-time data and predictive analytics, organizations can respond faster to demand fluctuations, supply disruptions, and changing market conditions [21]. For example, AI-powered forecasting systems enable firms to anticipate customer demand more accurately and adjust production and inventory plans accordingly. Such responsiveness and agility are essential for maintaining a competitive advantage, particularly in dynamic and uncertain supply chain environments [32].

In addition, DSC practices support superior customer service by ensuring product availability, timely delivery, and consistent quality control. Technologies such as blockchain enhance supply chain transparency by providing verifiable information about product origins, production processes, and distribution channels, thereby strengthening customer trust [33]. The adoption of DSC practices has also been linked to improved financial performance through better resource utilization, lower operating costs, and increased revenue growth [5]. For example, big data analytics can identify inefficiencies in supplier performance and procurement processes, leading to significant cost savings. Consistent with these findings, empirical evidence indicates that firms with more advanced DSC capabilities outperform their competitors on key financial performance indicators [25]. DSC practices allow companies to examine new technologies and business models, promoting innovation and long-term competitiveness. For example, companies can test scenarios and optimize operations prior to implementation by using digital twins, which are virtual representations of physical supply chain activities [2]. Supply chain skills increase the positive effect of IT deployment on performance, even though they do not directly enhance performance [34]. Organizations that use DSC technologies have a longer-lasting competitive edge because they are better equipped to adapt and react to new market trends [6]. However, despite the recognized advantages of DSC methods, several gaps remain in the literature. For example, little is known about the mediating elements that affect the relationship between DSC practices and performance [25]. In this sense, the third hypothesis of this study is to examine the impact of DSC practices on organizations' performance, as follows:

- H3: DSC practices positively influence OP.

G. The Mediation Role of DDDM in the Relationship Between DSC Practices and OP

The effects of DSC practices on performance are not automatic. According to earlier research, when businesses lack sufficient governance frameworks or analytics-oriented decision cultures, digital technologies may result in data overload, low-quality information, or superficial analytics use [8, 10]. Increased data accessibility may impede rather than improve managerial decision-making in such circumstances.

Thus, DDDM is conceptualized in this study as a crucial organizational process that determines whether DSC practices result in performance gains. DSC practices create value through a sequential decision-making process in which data are first generated and integrated across supply chain activities, then analyzed to produce actionable insights, and finally translated into managerial decisions that shape operational outcomes and overall firm performance [7, 8, 11, 13]. This process-oriented perspective emphasizes that the performance benefits of DSC practices are not automatic; rather, they depend on organizational capabilities that support effective data interpretation and evidence-based decision-making under conditions of heightened information-processing demand [10]. These findings indicate that DDDM enhances OP by aligning data-driven strategies with corporate objectives and transforming technological innovations into actionable insights. According to [28], companies that implement DDDM claim increases in operational efficiency, cost optimization, and responsiveness to market dynamics. Additionally, authors in [35] highlighted that leveraging analytics and data-driven strategies enhances both customer satisfaction and financial performance. Despite evidence supporting the mediating role of DDDM, there is a lack of comprehensive frameworks that examine how specific DSC practices interact with DDDM to influence different dimensions of OP [24]. Thus, this study proposes a fourth hypothesis to investigate the mediating role of DDDM in the relationship between DSC practices and OP, as follows:

- H4: DDDM mediates the relationship between DSC practices and OP.

The proposed research framework includes DSC practices as an independent variable, DDDM as a mediator variable, and the organization's performance as a dependent variable. The development of the research framework came in line with the previous DSC practices' empirical studies [18]. Besides that, it is consistent with the Resource-Based View (RBV) theory, according to which sustaining organizations' performance is connected to their internal resources [36]. The proposed model is shown in Figure 1:

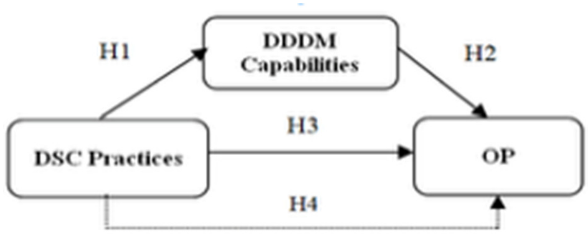

Fig. 1. The proposed model of the study's variables.

Few empirical frameworks have examined the mediating role of DDDM in the relationship between DSC practices and OP. By testing the proposed research hypotheses using a sufficiently large sample, the present study seeks to address this gap in the literature by examining the total effect of DSC practices on OP, incorporating both direct and indirect effects. Therefore, the study aims to answer the following research questions:

- Do the Egyptian Food and beverage organizations recognize the importance of applying DSC practices?
- Do the DSC practices significantly affect the OP of the Egyptian food and beverage organizations?
- Do the DDDM significantly impact the organization's performance?
- Does the DDDM play a significant role in the relationship between DSC practices and organizations' performance?

Research Method

H. Sample and Procedure

The study employed a purposive sampling method to ensure the inclusion of respondents with relevant professional knowledge and practical experience in operations and supply chain management. The sample was selected through several steps, including: First, establishing a framework for the target research population by identifying companies operating in the food and beverage sector in the Arab Republic of Egypt. Second, targeting employees within these organizations working in operations, logistics, supply chains, purchasing, warehousing, and information systems, as well as those in related administrative roles involving digital technology and supply chain decision-making. Third, contacting the selected participants through professional networks, LinkedIn, direct communication, and email to confirm their participation in the survey.

The sample size was determined using the standard sampling equation proposed by [37]. A confidence level of 95% (z = 1.96) was adopted, with a conservative sample proportion of 50% and a margin of error of ±5%. Based on these parameters, the required sample size, independent of the population size, was estimated at approximately 385 respondents. A total of 420 questionnaires were distributed to employees with relevant knowledge and experience in operations and supply chain management. After excluding 54 responses due to missing data, 366 valid questionnaires were retained for analysis, resulting in an effective response rate of approximately 87%. Before the main data collection, a pilot study comprising 40 questionnaires (representing 10% of the required sample size) was conducted to assess the validity and reliability of the measurement instrument and to identify potential issues during the fieldwork. Based on the pilot results, necessary refinements were made before administering the full-scale survey. Additionally, Harman's single-factor test was used to evaluate the presence of common method bias. The results showed that the largest single factor accounted for 41% of the total variance, which is below the proposed threshold of 50%, indicating that common method bias was not a concern in this study.

I. Measurement

The questionnaire consisted of two main sections. The first section collected background information about the respondents and their organizations, including the area of operation within the industry, years of experience, organizational role, and firm size. The second section contained the measurement scales for DSC practices, DDDM, and OP. To develop the survey instrument, an extensive review of the supply chain management and information technology literature was conducted, and the content validity approach, proposed in [38], was followed. First, in-depth interviews were conducted with five Chief Operating Officers (COOs) from the Egyptian food and beverage industry to gain practical insights into DSC practices and DDDM based on their professional experience. Second, the initial version of the questionnaire was refined through discussions with several academic experts. Finally, a pre-test involving 20 business professionals was carried out to identify potential issues and to further improve the clarity, relevance, and structure of the questionnaire. The final questionnaire was administered in both English and Arabic. Measurement items for DSC practices were adapted and modified based on prior studies [4, 25, 39, 40]. The five DSC items assessed the firm's capability to manage supply chain operations using advanced digital technologies, including blockchain, the IoT, big data analytics, and AI. Following the recommendations of [41], the measurement items for DDDM were adopted and tailored based on [42, 43] and were further aligned with DSC practices. OP, the dependent variable, was measured using five items adapted from [44–46]. All measurement items for DSC practices, DDDM, and OP were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Data collection was conducted between April 2025 and July 2025.

J. Sample Profile

Table I illustrates the 366 respondents' data profiles.

TABLE I. SAMPLE CHARACTERISTICS

Sample profile (valid n= 366)		N	%
Primary area of operation within the Industry	Food manufacturing	174	47.2%
	Retail (e.g., supermarkets, specialty stores)	75	20.4%
	Distribution and logistics	72	19.4%
	Beverage production	34	9.3%
	Hospitality (e.g., restaurants, catering)	11	3.7%
Total		366	100%
Years of Experience	More than 10 years	156	42.6%
	Years (1 - 5)	78	21.3%
	Years (6 - 10)	71	19.4%
	Less than 1 year	61	16.7%
Total		366	100%
Primary role in the organization	Operations	118	32.4%
	Strategic planning	77	21.3%
	Logistics	77	21.3%
	Technology/ IT	43	12.0%
	Sales	22	4.6%
	Purchasing	13	3.7%
	Finance	10	2.8%
	Quality	6	1.9%
Total		366	100%
Firm size	More than 1000	179	49.1%
	251 – 1000	105	28.7%
	50 – 250	43	12.0%
	Less than 50	39	10.2%
Total		366	100%

The primary area of operation within the industry involved: 174 (47.2%) for food manufacturing, 75 (20.4%) for retail, 72 (19.4%) for distribution and logistics, and 45 (13%) for beverage production and hospitality. The sample's participants who had experience for more than 10 years were 156 (42.6%), for (1 - 5) years 78 (21.3%), for (5 – 10) years 71 (19.4%), and for less than one year 61 (16.7%). The respondents' primary role in the organization entailed: 118 (32.4%) in operations, 77 (21.3%) in strategic planning, 77 (21.3%) in logistics, 43 (12%) in technology/ IT, 22 (4.6%) in sales, 13 (3.7%) in purchasing, and 10 (2.8%) in finance and quality 6 (1.9%). Regarding firm size, 179 (49.1%) had more than 1000 employees, 105 (28.7%) had 251-1000 employees, 43 (12%) had 50 – 250 employees, and 39 (10.2%) had less than 50 employees.

III. RESULTS

SEM was employed as the primary statistical analysis technique, as it is widely used and well-suited for testing complex research models [38]. The study model was evaluated using SmartPLS for several reasons. First, SmartPLS minimizes the residual variances of endogenous variables. Second, it is effective for analyzing complex models involving multiple constructs and indicators. Third, it facilitates the examination of causal relationships and predictive capabilities, particularly in marketing and management research. Finally, compared with Covariance-Based SEM (CB-SEM), SmartPLS is more robust in handling issues related to multicollinearity and non-normal data distributions [47]. The statistical analysis was conducted in two stages. In the first stage, the reliability and validity of the measurement model were assessed. In the second stage, the structural model was evaluated to test the hypothesized relationships [47].

A. Measurement Model Evaluation (MME)

At this stage, the measurement model was evaluated by assessing Internal Consistency Reliability (ICR), Convergent Validity (CV), and Discriminant Validity (DV). Following the guidelines of [48], factor loadings greater than 0.6 were considered acceptable. The results confirmed that all measurement items exhibited factor loadings exceeding this threshold, as presented in Table II. The Kaiser–Meyer–Olkin (KMO) measure was also applied to assess sampling adequacy. KMO values range from 0 to 1, with higher values indicating stronger convergent validity. The cumulative variance explained by the constructs was 65.562% for DSC practices, 65.166% for DDDM, and 67.315% for OP, with all KMO values exceeding the minimum acceptable threshold of 0.50. Construct reliability was examined using Cronbach's alpha and Composite Reliability (CR). All constructs achieved values greater than 0.70, indicating satisfactory internal consistency [49]. CV was further assessed through the Average Variance Extracted (AVE), with all constructs demonstrating AVE values above 0.50, thereby confirming adequate CV [50], as depicted in Table II.

DV was assessed by comparing the square root of AVE for each reflective construct with its correlations with other constructs, as presented in Table III. In all cases, the square root of AVE exceeded the corresponding inter-construct correlations, satisfying the criterion proposed in [50], and confirming adequate DV. Overall, the results reported in Tables II and III indicate that the measurement model demonstrates satisfactory ICR, CV, and DV.

TABLE II. CV AND ICR

Construct/indicators	Loading	Cronbach's α	CR	AVE
DSC:		0.798	0.808	0.555
DSC1	0.771			
DSC2	0.814			
DSC3	0.696			
DSC4	0.667			
DSC5	0.766			
DDDM:		0.793	0.807	0.551
DDDM1	0.662			
DDDM2	0.704			
DDDM3	0.871			
DDDM4	0.684			
DDDM5	0.772			
OP:		0.878	0.880	0.673
OP1	0.823			
OP2	0.839			
OP3	0.802			
OP4	0.849			
OP5	0.786			

TABLE III. DV ACCORDING TO FORNELL AND LARCKER'S (1981) CRITERION

1. DSC	2.DDDM	3. OP
0.745		
0.695	0.742	
0.622	0.7	0.82

B. Structural Model Evaluation

The structural model, as depicted in Figure 2, was evaluated using a bootstrap resampling procedure conducted in four sequential steps. First, multicollinearity was assessed using the Variance Inflation Factor (VIF). All VIF values ranged from 1.34 to 2.64, which is below the proposed threshold of 5, indicating that multicollinearity was not a concern [38].

Second, the model's predictive power was examined by evaluating the coefficient of determination (R^2). The R^2 values for the endogenous constructs were 0.483 for DDDM and 0.526 for OP. Both values exceed the minimum proposed level of 10%, suggesting strong predictive capability [51]. Third, the significance of the structural path coefficients was assessed using a bootstrapping procedure with 5,000 subsamples at a 5% significance level [38, 48]. Finally, the predictive relevance of the model was evaluated using the Stone–Geisser Q^2 statistic. The Q^2 values for DDDM (0.463) and OP (0.358) were greater than zero, indicating that the exogenous constructs possess adequate predictive relevance for the endogenous variables.

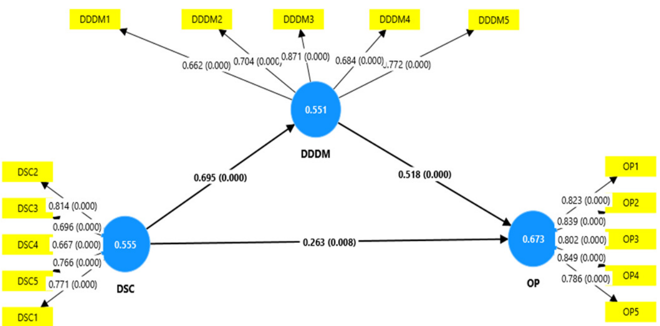

Fig. 2. Results of SmartPLS path model.

The overall fit of the structural model was assessed using the Standardized Root Mean Square Residual (SRMR). The SRMR value was 0.064, which is below the proposed threshold of 0.08, indicating an acceptable model fit [52]. In addition, the Goodness-of-Fit (GoF) index was calculated using the equation proposed in [53]. Based on the model's R^2 and AVE values, the GoF value was 0.547, which exceeds the proposed cutoff value of 0.26, further confirming that the structural model demonstrates a good overall fit.

C. Testing of Hypotheses

The proposed hypotheses were tested by estimating the structural path coefficients, as illustrated in Tables IV and V. A bootstrapping procedure with 5000 subsamples at a 5% significance level was applied to compute standard errors, t-values, and p-values for hypothesis testing [38, 48]. The results indicate that DSC practices have a positive and significant effect on DDDM ($\beta = 0.262$, $p < 0.05$), supporting H1. In addition, DSC practices exert a positive and direct impact on OP ($\beta = 0.695$, $p < 0.05$), thereby supporting H2. Furthermore, DDDM has a positive and statistically significant influence on OP ($\beta = 0.518$, $p < 0.05$), confirming H3.

TABLE IV. HYPOTHESES TESTING RESULTS OF DIRECT EFFECTS

Direct effects	PC	SE	95% CIB	t-value	p-value	Support
H1	0.262	0.05	(0.613-0.777)	2.393	0.008	Yes
H2	0.695	0.109	(0.082-0.442)	13.877	0	Yes
H3	0.518	0.089	(0.372-0.665)	5.829	0	Yes

Table V displays the results of the mediation hypotheses. The results demonstrate that DDDM partially mediates the relationship between DSC and OP. Specifically, the indirect effect of DSC on OP through DDDM was found to be positive and statistically significant ($\beta = 0.351$, $P<0.05$). This pattern confirms the presence of partial mediation, thereby supporting H4. Accordingly, the research hypotheses are supported. While the results support the proposed relationships, their strength and manifestation are likely varied across contexts. Industries with lower environmental uncertainty, stronger institutional support, or higher data governance maturity may experience smaller marginal advantages from DSC practices because information-processing demands are less prominent. In contrast, in highly volatile or perishable-product industries, such as food and beverage, the importance of DDDM as a coordinating mechanism is salient.

TABLE V. HYPOTHESES TESTING RESULTS OF INDIRECT EFFECTS

Indirect effects	PC	SE	95% CIB	t-value	p-value	Support
H4	0.351	0.073	(0.233-0.473)	4.987	0	Yes

IV. CONCLUSIONS, IMPLICATIONS, AND LIMITATIONS

A. Conclusions

Using a survey-based approach, this study examined the relationships among Digital Supply Chains (DSC) practices, Data-Driven Decision-Making (DDDM), and Organizational Performance (OP), with a specific focus on the Egyptian food and beverage industry. The findings provide strong empirical evidence that DSC practices positively influence DDDM, complying with [20], which highlights the role of digital supply chain initiatives in enhancing collective and data-informed decision-making processes. These results are also consistent with [2, 19], which emphasize that digital systems improve the accuracy, quality, and reliability of data-driven decisions. In addition, the study confirms that DSC practices have a positive and significant impact on OP. This finding aligns with [4], demonstrating that digital supply chain technologies enhance both financial and operational outcomes in manufacturing and related industries. As a result, organizations that effectively leverage digital technologies in supply chain management can achieve improved resource utilization, lower operating costs, and increased revenue growth [5]. Supporting this conclusion, empirical evidence indicates that firms with more advanced DSC capabilities outperform their competitors on key financial performance indicators [25]. Furthermore, the results support the hypothesis that DDDM positively influences OP. This finding is consistent with prior studies identifying DDDM as a critical determinant of performance outcomes [24]. The ability to systematically incorporate data-driven insights into managerial decision-making enables organizations to improve operational efficiency and enhance strategic decision quality. Finally, this study examined the mediating role of DDDM in the relationship between DSC practices and OP. The findings reveal that DDDM partially mediates this relationship, underscoring the importance of data-driven decision processes in translating digital supply chain investments into performance gains. Organizations in Egypt’s food and beverage sector can leverage DSC practices, supported by robust DDDM capabilities, to achieve superior operational and financial outcomes.

B. Implications

This study provides several theoretical and practical contributions. First, it empirically validates how DSC practices enhance OP, contributing to the theoretical literature by developing novel evaluation metrics for DSC and DDDM. By refining these metrics, the study offers a greater understanding of how organizations would integrate DSC strategies with DDDM. Second, the findings emphasize that digital transformation should not be viewed as an isolated initiative but as an embedded strategic function essential for maintaining competitive advantage. This insight serves as a critical reminder for decision-makers that digitalization should be integrated at the strategic level rather than treated as a standalone business application. From a practical perspective, the study provides valuable insights for the food and beverage industry in Egypt, highlighting the role of DSC practices in sustaining organizational value. Therefore, firms should adopt these practices strategically to realize their full potential. Furthermore, the study addresses the challenges associated with emerging technologies and the increasing volume of data in supply chain decision-making. By presenting effective quantitative and qualitative data analysis approaches, this research contributes to the advancement of smarter, more DDDM in supply chain management. Managers can use these insights to create practical decision-making guidelines, including:

- Set up protocols for gathering, analyzing, and applying supply chain data to make strategic decisions.
- Integrate digital initiatives into strategic planning sessions and tie them to long-term performance goals.
- Implement organized quantitative and qualitative data analysis techniques to create more informed, evidence-based decisions
- Give strategic priority to DSC projects that complement company objectives and the local market context.

C. Limitations

The limitations of this study also suggest directions for future research. First, the research focuses exclusively on Egypt's food and beverage industry, which may limit the applicability of the findings to other economic, regulatory, or technological contexts. Future studies could therefore examine broader environments to gain greater insights. Second, the study employed a cross-sectional survey design, which may introduce biases and limit the ability to assess causal relationships. Future research could adopt longitudinal designs or mixed-method approaches to address this limitation. Third, this study conceptualizes DSC practices as a higher-order construct that aggregates multiple digital technologies (e.g., Artificial Intelligence (AI), Internet of Things (IoT), blockchain). While this approach is theoretically grounded in the Resource-Based View (RBV), it may obscure technology-specific effects. Consequently, the findings reflect the combined influence of an integrated digital resource bundle rather than the impact of individual technologies. Finally, the study relies on available data sources, which may be biased, incomplete, or inconsistent. Differences in data collection methods across organizations could affect the accuracy and generalizability of the results.

D. Future Research Directions

To address these limitations, future research could explore several directions. Studies could examine the potential nonlinear or threshold effects of DSC activities, particularly in contexts with low data maturity or weak analytics cultures. Research could also investigate the impact of real-time data integration on DSC efficiency and leverage more advanced predictive analytics and AI-powered models. Additionally, longitudinal studies are needed to assess the long-term effectiveness of DDDM in digital supply chains.

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