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Role of Data Analytics in Agriculture Supply Chains: Exploring the role of Digital Transformation Success Factors

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Abstract

The present study examines how data-driven technologies and organisational enablers collectively enhance agricultural supply chain performance in Northern India. Digital transformation driven by tools such as IoT, artificial intelligence, and big data analytics has been reshaping traditional farming into an intelligent data-centric ecosystem. This research investigates the influence of key DT success factors, i.e., culture, technology, customer orientation, and human skills & capabilities on agricultural supply chain performance. A structured questionnaire survey was conducted among 900 respondents from the northern Indian states of Punjab, Haryana, and Jammu & Kashmir. The study employs Smart-PLS-SEM analysis to evaluate the relationships among key constructs. Findings reveal that all four success factors significantly and positively influence agricultural supply chain performance. The results underscore that data analytics enables farmers and supply chain stakeholders to make informed, data-driven decisions that optimise productivity, resource utilisation, and sustainability. Furthermore, the integration of technologies such as IoT, AI, and predictive analytics enhances transparency, traceability, and resilience across the supply chain. This study contributes to the growing discourse on digital agriculture by providing empirical evidence that data analytics serves not merely as a tool but as a strategic enabler of transformation, supporting policymakers and practitioners in advancing rural digital ecosystems.

Keywords: *Data Analytics, Agriculture Supply Chains, Digital Transformation*

Introduction

Digital transformation in agriculture plays a vital role in enhancing productivity, sustainability, and decision-making processes, particularly using big data and analytics. This transformation is driven by the amalgamation of modern technologies such as IoT, big data and analytics that may tackle the challenges faced by the Indian agriculture sector (Di & Zhu, 2024). Digital transformation in agriculture represents a paradigm shift as digital technologies and data analytics fundamentally reshape agricultural practices that may improve the productivity, sustainability, and efficiency. Integrating advanced modern technologies such as the IoT, artificial intelligence, data analytics etc. enables farmers to adopt farming techniques that may be the result of data-driven decision-making (Gong & Ribiere, 2021; Schallmo & Williams, 2018). Through these digital advancements, agriculture is evolving from traditional methods to a more innovative and efficient that may be capable of addressing challenges like climate change, resource insufficiency, and food related problems (Sargani et al.,2025; Jones et al., 2021). Precision farming is one of the important applications of digital transformation in agriculture

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where IoT devices like sensors, GPS, and drones gather real-time data on soil condition, climate patterns, crop wellbeing, and pest infestations (Andiyappillai, 2020; Albukhitan, 2020). The data is processed and analyzed help farmers to optimize allocation of resources that may increase yields and decrease costs as well (Ângelo et al., 2017). For instance, AI equipped tractors and GPS helps in high precision thus, minimising labour costs and improving efficiency (Schmutz et al., 2016). This technology integration boosts productivity as well as conserves essential resources and promotes environmental sustainable practices (Gao et al., 2022).

Digital transformation like data analytics also plays a pivotal role in monitoring crop health. Tools like drones, satellites etc enable farmers to assess crop growth and identify issues such as diseases, pests, or nutrient deficiencies early on (Chouhan, Thapa & Choudhury, 2024). Interventions based on real-time data can prevent crop losses and ensure optimal yields (Gao et al., 2022). The ability to monitor crops remotely enhances resilience by enabling farmers to respond quickly to adverse conditions (Schilirò, 2021). Additionally, predictive analytics and machine learning models support farmers in assessing long-term patterns and trends, facilitating better planning and adaptation to changing environmental conditions (Kraus et al., 2022). Digital transformation also increases transparency and traceability in the agricultural supply chain which is an area of growing importance to consumers. By using data analytics, stakeholders can monitor the processes of agricultural products from farm to table, ensuring increased efficiency and reducing waste (Jones et al., 2021).

Furthermost, as agriculture embraces digital transformation, it faces both opportunities and challenges. Digital agriculture holds immense potential for revolutionizing traditional farming, enhancing productivity, and promoting sustainable practices (Schallmo & Williams, 2018). However, effective implementation requires significant investment in digital infrastructure, such as high-speed internet access, especially in rural areas. Digital literacy is also essential for all the stakeholders especially farmers in this case must be trained to use new technologies effectively (Karunanayaka et al., 2020). Additionally, supportive policies and regulatory frameworks are crucial in the adoption of digital technologies in the agricultural sector thus, encourage innovations (Schilirò, 2021). Hence, the integration of big data and analytics in agriculture is driving digital transformation, providing a pathway to more efficient and resilient farming processes. As digital technologies continue to advance, their application in agriculture is likely to expand, offering further opportunities for optimizing resource management, enhancing crop monitoring, and improving supply chain transparency (Gong & Ribiere, 2021; Kraus et al., 2022). Thus, the objective of this paper is to comprehend the role of data analytics in transforming agriculture supply chains and to empirically explore the impact of digital transformation success factors on agriculture supply chains.

Review of Related Literature

A literature review surveys existing research in a specific field, providing an overview of the current knowledge and drawing conclusions on its advancements.

Role of big data and analytics in digital transformation

Digital transformation is a pivotal concept in the ongoing modernisation of agriculture, driven by technological advancements and the urgent need to address challenges like improving supply chains and environmental sustainability. Although digital transformation encompasses a wide range of initiatives, it generally refers to integrating digital technologies to enhance productivity, resilience and sustainability in agricultural practices. Westerman et al. (2011) describes digital transformation as an approach through which agriculture can enhance performance by leveraging digital tools, such as data analytics, mobile platforms, social media, and smart embedded devices. The implementation of these technologies empowers agricultural businesses to develop innovative value propositions, streamline processes, and improve stakeholder relationships (Westerman et al., 2014). Leading agricultural firms are increasingly adopting digital technologies to reshape conventional methods, with data-driven insights guiding decisions on crop management, resource allocation, and market engagement (Henriette et al., 2015; Schallmo & Williams, 2018).

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Initially, the focus of digital transformation in agriculture was centred on the technological adoption of tools like big data, IoT, and mobile platforms. However, Goran et al. (2017) and Henriette et al. (2015) emphasise that the scope has expanded to include cultural shifts within organisations. For digital transformation to be effective there must be an alignment between technology adoption and organisational factors such as leadership, talent, and cultural adaptability (Ross et al., 2016). The integration of social media, mobile platforms, and data analytics not only transforms agricultural practices but also necessitates new management approaches that can navigate these complex changes (Schallmo & Williams, 2018). The recent pandemic also accelerated digital transformation among industries that include agriculture, compelling organizations to embrace digital tools to address disruptions in supply chains, labour shortages, and market instability (Jones et al., 2021). As also emphasised by Agrawal et al. (2020), the pandemic hastened digital adoption to reduce physical interactions, reflecting a broader trend toward remote operations and digital engagement. Consequently, investments in AI and mobile applications have become instrumental in mitigating agricultural challenges, reshaping the consumer behaviours and thus, fostering resilience (World Economic Forum, 2020). Digital transformation may exacerbate inequalities, as smaller farms struggle to keep up with larger agribusinesses in adopting new technologies. Thus, in order to ensure equitable access to digital resources, it is essential for promoting inclusive growth within the sector (Schilirò, 2020). Beyond organizational improvements, digital transformation in agriculture also involves redesigning business processes. Westerman et al. (2014) highlight that the use of technology radically enhance organizational performance involves optimizing processes and restructuring operations. Verhoef et al. (2021) argued that three factors drive the need for digital transformation i.e. the proliferation of digital infrastructure like the internet and smartphones, shifting competition dynamics in favour of digital innovation and evolving consumer behaviours. These factors are reshaping agricultural markets and supply chains, encouraging agricultural firms to innovate in response. Zekic-Susac, Mitrovic, and Has (2021) emphasized that digital transformation poses challenges for entire economies, requiring coordinated policy efforts. Manfreda, Ljubi, and Groznik (2021) also suggested that governments can glean valuable insights from digital experiments in smart cities and villages to foster a digitally integrated agricultural society that benefits all stakeholders.

Role of big data and analytics in agriculture supply chains

The agriculture sector has long been a cornerstone of global economies, playing an important role in safeguarding food security thus, contributing to rural livelihoods. As the total population is projected to exceed nine billion by 2050 (Gilpin, 2015), the need for food will rise significantly, placing tremendous pressure on agricultural systems to increase productivity while reducing environmental impacts. Consequently, technological innovations, particularly the integration of big data and analytics becomes pivotal in revolutionizing modern agricultural practices to address these challenges. Furthermost, it also helps farmers in data-driven decisions that may increase crop production, lessen wastage of resources and improve overall efficiency.

Success Factors of Digital Transformation

The digital transformation of agricultural supply chains is influenced by several dimensions, including culture, technology, customer focus, and human skills & capabilities. Each of these dimensions is essential for enabling the integration of data analytics to improve efficiency, responsiveness and sustainability in agriculture.

Cultural Dimension and Digital Transformation (DT) in Agriculture

Organizational culture significantly impacts the adoption of digital transformation in agricultural supply chains. A culture that values data-driven practices, innovation, and adaptability is essential for integrating digital tools and big data analytics in agriculture (Avgerou, 2001). For example, when supply chain actors embrace a shared goal of innovation, they are more likely to use analytics for demand forecasting, yield optimization, and resource management, which enhances the overall supply chain's effectiveness (Cameron & Quinn, 2006). Research highlights that fostering a culture open to technological change is key to successful digital adoption in agriculture, enabling more resilient supply chains (Baird & Raghu, 2015).

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Technological Dimension and Digital Transformation (DT) in Agriculture

The technological dimension is a critical driver of digital transformation in agriculture, as advanced tools like IoT, AI, and data analytics enable precision agriculture facilitates informed decision-making (Bharadwaj et al., 2013). With strong technological infrastructure, agricultural supply chains can leverage real-time data for crop health monitoring, logistics optimisation, and predictive maintenance (Chen et al., 2012). These tools enhance operational efficiencies, improve yield prediction accuracy, and reduce resource waste, all essential for sustainable agricultural practices (Verma et al., 2020).

Customer Dimension and Digital Transformation (DT) in Agriculture

Customer-centric strategies play a vital role in successful DT, especially when aligning agricultural supply chains with consumer demands (Al-Debei et al., 2015). Big data analytics allows agricultural supply chains to better understand and predict market needs, enabling responsive supply chains that can adapt to customer preferences and seasonal demand shifts (Lee et al., 2015). By using analytics to improve product quality, traceability, and delivery timelines, agricultural organizations can strengthen relationships with consumers and enhance brand loyalty (Wedel & Kannan, 2016).

Human Skills and Capabilities Dimension and Digital Transformation (DT) in Agriculture

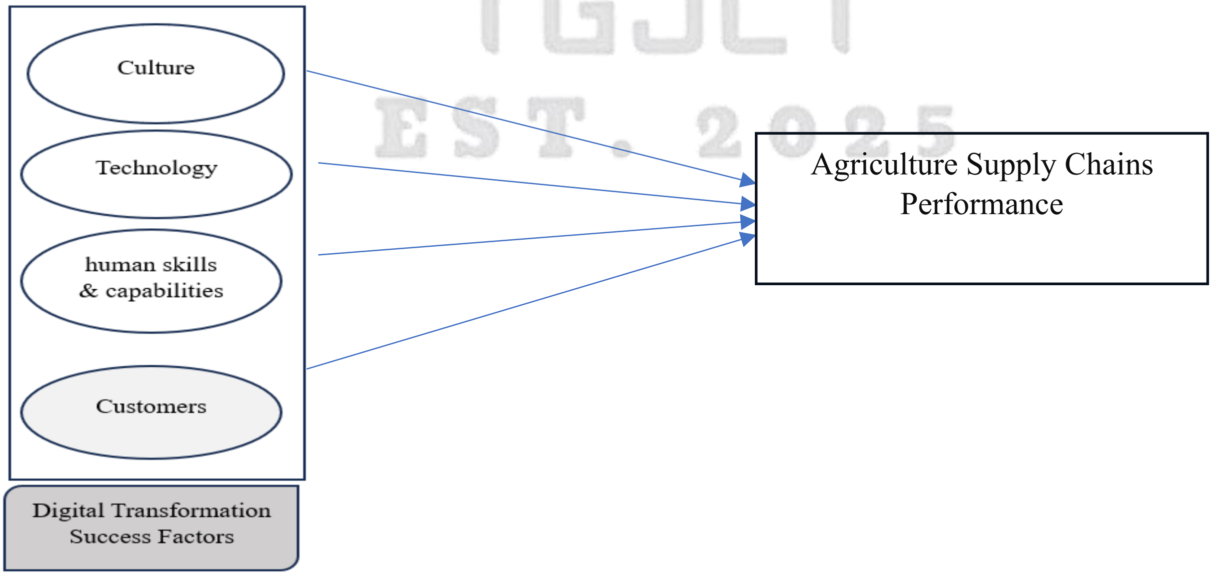
Human capital is essential for managing digital transformation in agricultural supply chains, as employees need skills in data analysis, digital tools, and decision-making (Laumer et al., 2020). Investing in digital literacy and training enables workers to make data-informed decisions that enhance supply chain resilience and efficiency (Bughin et al., 2017). Developing a workforce with expertise in big data analytics supports innovation and agility, allowing organizations to quickly respond to market changes and environmental factors affecting agriculture (Davenport & Harris, 2017).

Hypotheses of the study

Based on the literature review and after understanding the role of data analytics in agriculture supply chains, the following hypotheses have been framed:

1. Culture has positive impact on Agricultural Supply Chains Performance.
2. Human skills and capabilities have positive impact on Agricultural Supply Chains Performance.
3. Customers has positive impact on Agricultural Supply Chains Performance.
4. Technology has positive impact on Agricultural Supply Chains Performance.

Research Framework Model



Source: **Bumann, J., and Peter, M.K. (2019), Singhdong, P. et.al. (2021)**

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Research Methodology

The research methodology is structured to establish a comprehensive framework for identifying and analysing the success factors of digital transformation and their impact on agricultural supply chain performance. The study focuses on farmers from the northern regions of India—specifically Punjab, Haryana, and the Jammu region of the Union Territory of Jammu and Kashmir. A total of 900 respondents were selected using a multi-stage random sampling technique to ensure representativeness. Primary data were collected through a structured questionnaire designed to capture respondents' perceptions of digital transformation success factors and their influence on agricultural supply chain performance. In addition, secondary data were obtained from various credible sources, including books, research journals, annual reports, newspapers, magazines, websites, and both published and unpublished papers. The collected data were analysed using the Smart-PLS software, applying exploratory methods to validate the proposed research framework and examine the interrelationships among key constructs.

Data analysis and interpretation

Demographic profiles of the respondents (n=900)

The gender distribution of the respondents shows 60% female (540) and 40% male (360), ensuring fair representation of both genders. In terms of age, the respondents were categorized as follows: below 20 years (1.4%), 20–30 years (21.9%), 30–40 years (22.4%), 40–50 years (32.1%), and above 60 years (22.2%). Married individuals form the largest group, comprising 70% (630 respondents) of the sample. Separated or divorced individuals 6.4% (58), and others 2.1% (19). Farmers make up 46.7% (420 respondents), highlighting the community's reliance on agriculture. Self-employed individuals constitute 18.6% (168), reflecting entrepreneurial activities. Business professionals account for 5.8% (51), government employees 20.6% (185), and the other category 8.3% (75). Individuals earning less than 1 lac comprise 16% (142 respondents), while those in the 1–2 lac bracket make up 33.3% (300). The 2–3 lac category accounts for 24.2% (218), and the 3–4 lac group represents 26.1% (235). Only 0.4% (5) of respondents earn 4 lac or more, highlighting a small high-income segment.

Structural Equational Modelling by Smart PLS- SEM

Factor Loadings

According to Henseler et al. (2009), since all indicator values are 0.5 or higher, it can be concluded that no items require deletion.

Constructs	Factor Loadings
CD1	0.817
CD2	0.816
CD3	0.872
CD4	0.862
CUL1	0.844
CUL2	0.878
CUL3	0.873
HS&C1	0.834
HS&C2	0.863
HS&C3	0.866

HS&C4	0.847
HS&C5	0.84
TECH1	0.792
TECH2	0.786
TECH3	0.824
TECH4	0.811
TECH5	0.796
TECH6	0.781
TECH7	0.81
TECH8	0.774
TECH9	0.709
TECH10	0.718
ASCP1	0.763
ASCP2	0.689
ASCP3	0.692
ASCP4	0.755
ASCP5	0.696
ASCP7	0.56
ASCP8	0.773
ASCP9	0.76
ASCP10	0.788
ASCP11	0.664
ASCP12	0.716
ASCP13	0.735
ASCP14	0.784
ASCP15	0.702
ASCP16	0.759
ASCP17	0.719

Construct Reliability and Validity

According to Nunnally (1978) and Jöreskog (1971), certain criteria must be fulfilled to assess construct reliability and validity. Specifically, the Cronbach's Alpha value should be at least 0.6 or 0.7, and the Composite Reliability (CR) should also be 0.6 or higher. Additionally, Rho_a should exceed 0.7, and the Average Variance Extracted (AVE) should be 0.5 or greater, as per Fornell and Larcker (1981). In this study, all constructs meet these criteria, indicating that the model demonstrates both construct reliability and validity.

Table 2: Construct Reliability and Validity

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CUL	0.832	0.832	0.899	0.749
TECH	0.929	0.929	0.94	0.61
HS&C	0.904	0.905	0.929	0.722
CD	0.863	0.866	0.907	0.709
ASCP	0.939	0.942	0.946	0.525

Discriminant Validity

According to Henseler et al. (2015), the HTMT criterion should be less than or equal to 0.85 or 0.90. The values in this study meet this threshold, indicating the absence of discrimination

Table 2: Discriminant Validity

Variables	ASCP	CD	CUL	HS&C	TECH
ASCP					
CD	0.785				
CUL	0.872	0.676			
HS&C	0.827	0.619	0.689		
TECH	0.84	0.608	0.765	0.745	

Collinearity Statistics

According to Hair et al. (2016), multicollinearity is not a concern if the Variance Inflation Factor (VIF) is below 5. Since all indicator values in this study fall within this limit, it indicates that multicollinearity is not an issue.

Table 4: Variance Inflation Factor

Items	VIF
ASCP1	2.651
ASCP2	2.516
ASCP3	2.442
ASCP4	2.708
ASCP5	1.973
ASCP7	1.443
ASCP8	2.829
ASCP9	2.823
ASCP10	2.926
ASCP11	2.222
ASCP12	2.68
ASCP13	2.5
ASCP14	2.775
ASCP15	2.618
ASCP16	3.18
ASCP17	2.857

CD1	1.9
CD2	1.928
CD3	2.503
CD4	2.348
CUL1	1.698
CUL2	2.11
CUL3	2.112
HS&C1	2.472
HS&C2	2.72
HS&C3	2.571
HS&C4	2.474
HS&C5	2.354
TEC1	2.462
TEC2	2.569
TEC3	3.16
TEC4	2.649
TEC5	2.454
TEC6	2.279
TEC7	2.617
TEC8	2.215
TEC9	1.769
TEC10	1.758

R-Square

According to Falk and Miller (1992), R^2 values of 0.10 or higher indicate an acceptable level of variance explained for an endogenous construct. Since both R^2 values in this model exceed 0.10, it can be concluded that the model demonstrates strong explanatory power.

Endogenous variables	**R-square**	**R-square adjusted**
ASCP	0.827	0.825

Hypotheses Testing

According to Hair et al. (2021), hypotheses are supported if the p-values are less than 0.5. Since the p-values for all constructs in this study are below 0.5, it indicates that all six hypotheses are supported.

Relationship	**Path Coefficients**	**Standard deviation**	**T statistics**	**P values**	**Result**
CD -> ASCP	0.243	0.029	8.406	0.000	Supported
HS&C -> ASCP	0.24	0.031	7.679	0.000	Supported
CUL -> ASCP	0.201	0.036	5.63	0.000	Supported
TEC -> ASCP	0.248	0.035	7.146	0.000	Supported

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Conclusion

This study evaluates the impact of digital transformation success factors on agricultural supply chain performance in selected villages of northern India, offering valuable insights into the transformative potential of data analytics in rural agriculture supply chains. The research, based on a diverse sample of 900 respondents, highlights the substantial influence of cultural drivers, technology, human skills, and customer engagement on improving agricultural supply chain performance. The high explanatory value of the model, validated through significant path coefficients and the absence of multicollinearity, further reinforces the critical role of digital transformation leading to improved productivity. These findings underscore the importance of data analytics for sustainable agricultural development, providing a framework for policymakers and stakeholders to drive smart farming practices and digital integration within the agriculture sector. By embracing digital transformation, rural areas can foster economic growth, enhance supply chain resilience, and improve the livelihoods of farmers, ultimately contributing to rural prosperity.

Limitations

Despite its valuable findings, this study has certain limitations. First, the research is geographically constrained to northern India only, which may limit the generalizability of results to other regions with different socio-economic and technological contexts. The reliance on self-reported data from farmers introduces the potential for response biases, as respondents may misinterpret questions or feel inclined to give socially desirable answers. Another limitation is that the study focuses only on a set of predefined digital transformation factors (culture, technology, human skills, customer engagement), potentially overlooking other influential variables, such as policy incentives, government support, and environmental factors that also affect agricultural supply chain performance.

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