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Moderating the Role of Top Management Support among Decision Support System, Artificial Intelligence, and Supply Chain Performance

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Abstract
The study objective was to test the impact of decision support systems, and artificial intelligence on supply chain performance with the moderating effect of top management support systems of dairy products manufacturers. Quantitative data was collected from 300 dairy product manufacturing company employees. Cross-sectional research was employed to collect the data through a self-administered questionnaire employing a convenient sampling technique. The Structural Equation modeling results show that decision supports system dimensions (Key performance indicators and Critical success factors) significantly increasing the supply chain performance. Similarly, artificial intelligence also significantly increases the supply chain performance. Further moderating effect results show that top management support significantly strengthen the relationship of decision support systems dimensions, artificial intelligence, and supply chain performance. The results contributed that integrating decision support systems dimensions (Key performance indicators and Critical success factors) and artificial intelligence can significantly enhance supply chain performance, with top management support playing a crucial role in increasing these

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effects. This highlights the importance of strategic leadership and advanced technologies in achieving competitive advantages in supply chain management. The research distinctively examines the combined impact of decision support systems and artificial intelligence on supply chain performance. Furthermore, the study also tested the moderating effect of the top management support system which is considered to be a big contribution to the research novelty. This novel approach offers fresh insights into the strategic integration of decision support systems, artificial intelligence, and top management support for optimizing supply chain performance.

Keywords: Decision support system, Supply chain performance, Artificial intelligence, Critical Success factors.

Introduction

Supply chain performance (SCP) plays an important role in determining the success and competitiveness of organizations by influencing cost, customer satisfaction, and operational efficiency (Emon et al., 2024). An efficient supply chain ensures that goods and services are delivered at one time, meeting or exceeding expectations reducing lead times, and increasing customer satisfaction (L. Li et al., 2024). Efficient supply chain operations help reduce costs by improving resource utilization, reducing waste, and optimizing resources, which in turn contributes to higher profitability (Unhelkar et al., 2022). Furthermore, resources a more efficient supply chain enables firms to adapt more quickly to market changes, disruptions, and changes in customer demand (Y. Li et al., 2024). Historically, companies that excel in SCP can distinguish themselves by providing quality service, maintaining costs, and effectively managing changes in market conditions (Qader et al., 2022). Consequently, the importance of operations in the supply chain goes beyond operational profitability which contributes to greater organizational success.

Decision Support Systems (DSS) have become essential tools in today's supply chain management which is offering incredible value to improve SCP (Gupta et al., 2022). Using data analytics, predictive modeling, and real-time insights, DSS enables businesses to make informed decisions that increase business efficiency (Ivanov, 2021). The importance of DSS in supply chain operations is profound because it helps organizations to optimize inventory management, accurately forecast demand, and streamline logistics operations (Kumar et al., 2022) which increases the SCP. In addition, DSS facilitates effective risk management by identifying potential problems and recommending emergency plans which helps reduce downtime and ensure continuity in operations (Gupta et al., 2022). Integrating DSS into supply chain management not only improves decision-making but also empowers companies to rapidly adapt to market developments, creating a sustainable competitive advantage (Rani et al., 2021). With the increasing complexity of the global supply chain, DSS services that enable organizations to meet challenges such as demand fluctuations,

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supply chain disruptions, and evolving customer expectations are increasingly important to increase SCP (Y. Li et al., 2024). Therefore, study focused on impact of DSS on SCP.

Equally, Artificial intelligence (AI) plays a key role in improving supply chain efficiency by automating processes, improving accuracy, and enabling data-driven decision-making (Belhadi et al., 2024). AI technology such as machine learning, natural language processing, and robotics are used to optimize the various components of the supply chain (Al-Shboul, 2024). Therefore, AI can recognize patterns and predict future trends which enables companies to anticipate changes in demand and adjust their operations accordingly (Rashid et al., 2024). Furthermore, AI-powered systems improve supply chain visibility which enables real-time material tracking and more efficient route planning which reduces transportation costs and delivery times (Belhadi et al., 2024). AI also enhances risk management by quickly identifying potential problems and providing actionable insights to mitigate their impact on SCP (Wong et al., 2024). Integrating AI into the supply chain also leads to greater flexibility, flexibility, and responsiveness which is leading to increased SCP (Belhadi et al., 2024). Consequently, study focused on impact of AI on SCP.

Top management support (TMS) plays an important role in enhancing DSS to improve SCP (Chatterjee et al., 2022). When top management actively invests in and promotes the use of DSS to ensure appropriate resource allocation, a culture of data-driven decision-making is encouraged, which leads to acceptance of the program throughout the organization whose contributions help overcome resistance to change and encourage continuous improvement and innovation in supply chain processes (Quint et al., 2024). Through prioritizing DSS projects, top management can align technical capabilities with strategic objectives, resulting in more informed decisions, improved operational efficiency, and faster delivery times and effectiveness (Buzdugan & Capatana, 2021). Further empirical evidence by Yusuf and Kusrini (2021) that top management's commitment to digital transformation initiatives enhances an organization's ability to use AI for competitive advantage. A leadership focus on technology adoption, talent development, and change management is essential to realizing the full potential of AI to improve SCP (Som & Anyigba, 2022). These studies emphasized that TMS is an important factor in increasing the decision support system and AI which helps to increase the SCP.

Several studies have been conducted on the relationship between DSS, AI, and SCP. Extant studies have been conducted on the segregated impact of DSS and AI on SCP while ignoring the combined impact in one model (Al Dakheel et al., 2020; Hakimovich, 2024; Mondol, 2021; Ngo et al., 2024). Therefore, this study contributed to the impact of AI on SCP along with DSS. DSS provides a structured framework for collecting, processing, and analyzing vast amounts of data (Naskar et al., 2024) and AI can then be utilized to generate predictive insights and automate decision-making

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processes (Belhadi et al., 2024). This synergy allows for more precise demand forecasting, optimized inventory management, and efficient logistics operations (Al-Shboul, 2024). Furthermore, extant studies also mixed findings on the relationship of DSS, AI, and SCP. This shows that there is a need to test the relationship in other contexts. Top management systems played an important role in improving AI to increase SCP through strategically integrating AI technologies into operations (El Jaouhari & Hamidi, 2024; Eyo-Udo, 2024). These systems help identify key areas where AI can optimize processes, such as demand forecasting, inventory management, and logistics (Chatterjee et al., 2022). Therefore, this study contributed a TMS system as a moderating variable on the relationship of DSS, AI, and SCP. In other words, prior studies were also conducted on firm performance majorly (García-Martínez et al., 2023; Naser & Alavi, 2023) while ignoring the impact on SCP. Therefore, this study contributed to the impact of DSS and AI on SCP.

The rest of the paper was divided into four chapters. The literature review explores existing studies and theoretical frameworks; the research methodology outlines the approach and techniques used; the data analysis and results present the findings; the discussion and conclusion interpret the results and summarize the key insights.

Literature Review

Supply chain performance (SCP) is defined as the ability of suppliers to deliver products and services efficiently which meets customer expectations effectively while reducing costs and maximizing responsiveness to market changes experienced, and thereby contributing to the success and competitiveness of the organization as a whole (Unhelkar et al., 2022). On the other hand, SCP refers to the efficiency and effectiveness of an organization's supply chain in delivering goods and services to customers (Rad et al., 2022). An effective SCP reduces costs, improves customer satisfaction, and increases operational efficiency. Even though the ability to effectively manage the supply chain is a key requirement for companies looking to respond quickly to market changes and customer demand, SCP is directly linked to an organization's profitability and market share. SCP enable companies to reduce lead times, reduce inventory, and improve service levels, which are essential for customer loyalty and ongoing and existing competitive advantage comes into play with the organizations needed for value from understanding the factors influencing SCP to improve the performance of their supply chain and achieve sustainable growth (Kazmi & Ahmed, 2022). Empirical studies emphasized that SCP not only affects operational efficiency but also contributes significantly to long-term strategic success. Various factor helps to improve the supply chain performance but among those DSS and artificial intelligence (AI) are important indicators to increase the supply chain performance (Kazmi & Ahmed, 2022; Oubrahim et al., 2023).

Decision Support Systems (DSS) are interactive software systems designed to help

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organizations make informed decisions by combining data, sophisticated analytical models, and user-friendly interfaces (Soori et al., 2024). To provide deliverables foreign operations have been able to operate and be efficiently executed plays an important role (Soori et al., 2024). DSS is important in supply chain operations based on its ability to increase decision-making accuracy, reduce arbitrariness uncertainty, and improve operational efficiency. DSS improves supply chain performance by providing critical analytical tools and real-time data insights that make it easier to build decisions well (Amin & Ahmed, 2024). DSS combines big data with advanced algorithms to improve demand forecasting, inventory management, and logistics processes (Kayvanfar et al., 2024). This reduces processing time, improves resource utilization, and increases customer satisfaction (Bai, 2024). Through enabling companies to map situations and predict outcomes, DSS helps mitigate risks and improve overall supply chain speed and responsiveness. There are various dimensions of the DSS but among those key performance indicators and critical success is an important which helps to increase the supply chain performance (Kayvanfar et al., 2024).

The DSS component includes KPIs, quantifiable measures used to assess an organization's success in achieving specific goals. In supply chain management, KPIs such as order accuracy, delivery time, inventory turnover, and cost efficiency are important in performance analysis (Kayvanfar et al., 2024). A study by Gamme and Johansson (2015) emphasized that well-defined KPIs provide a clear framework for measuring supply chain activities, which helps to identify areas for improvement and improve overall performance. Arif et al. (2023) also emphasized that aligning KPIs with strategic objectives leads to better decision-making and SCP reinforcement. Other studies such as (Gualandris et al., 2015; Kalf et al., 2023) found that KPI implementation facilitates continuous monitoring and comparison of supply chain management, leading to increased transparency and accountability. The ability to monitor performance theoretically enables organizations to proactively respond to obstacles and maintain a competitive edge in the marketplace. Furthermore, (Rahiminezhad Galankashi & Mokhatab Rafiei, 2022; Tripathi & Roy, 2024) also stated that a balanced scorecard approach, with financial and non-financial KPIs, provides a comprehensive view of organizational performance and helps to align supply chain strategies with overall performance objectives evaluation to increase the supply chain performance. The implementation of KPIs Includes setting realistic goals, regular reviews, and developing a culture of accountability (Rahiminezhad Galankashi & Mokhatab Rafiei, 2022). In day-to-day operations, KPIs ensure that employees at all levels are aware of performance expectations and contribute to achieving organizational goals (Rahiminezhad Galankashi & Mokhatab Rafiei, 2022). KPIs are therefore an indispensable tool to enhance continuous improvement and SCP. Based on the above studies it is hypothesized that,

H1: Key performance indicators significantly influence the supply chain.

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Another important dimension of DSS is critical success factors. Critical Success Factors are the essential elements required for achieving desired outcomes in supply chain management (Sarangi & Ghosh, 2024). Factors such as supplier relationships, technology integration, process optimization, and skilled workforce have been identified as crucial for SCP (Tetteh et al., 2024). According to Rahiminezhad Galankashi and Mokhatab Rafiei (2022), understanding and focusing on CSFs enable organizations to prioritize resources and efforts toward activities that have the most significant impact on performance. Empirical studies by (Baah et al., 2022; Nguyen et al., 2022) indicate that strong supplier collaboration and effective communication are key drivers of supply chain success. They also stated that alignment of CSFs with organizational objectives ensures that supply chain initiatives are strategically targeted and yield tangible benefits. Further research highlighted the importance of risk management as a critical success factor (Joshi et al., 2024). Their study emphasizes that organizations that proactively manage risks through strategic partnerships and strong contingency planning are better positioned to maintain supply chain resilience and performance. Moreover, Patidar et al. (2023) suggested that incorporating sustainability practices into supply chain operations can serve as a critical success factor, contributing to long-term SCP by addressing environmental and social concerns. Following hypothesis is formulated based on the above,

H2: Critical Success Factors (CSFs) Significantly Influence Supply Chain Performance.

Artificial intelligence (AI) has transformed supply chain management by enabling data-driven decision-making, predictive analytics, and automation. AI technologies such as machine learning, natural language processing, and robotics have become increasingly important in advanced workflow (Nozari et al., 2022). Joshi et al. (2024) further confirmed that AI-driven solutions are effective in demand forecasting, inventory management, and logistics planning which is increasing SCP. The transformative capabilities of AI emphasize its critical role in achieving optimal SCP in the digital age. Furthermore, Belhadi et al. (2024) also highlighted that AI technology enables supply chains to be flexible and responsive to market changes. Through leveraging big data analytics, organizations could gain deeper insights into customer behavior, market trends, and business inefficiencies. Their research shows that AI-powered predictive analytics can help organizations identify potential problems and develop proactive mitigation strategies, ensuring continuity and resilience in SCP. Based on the above, the following hypotheses are formulated,

H3: Artificial Intelligence (AI) Significantly Influences Supply Chain Performance.

Moderating role of Top Management system

In the prior literature have been found that the relationship between DSS and SCP is not clear. Most of the extant studies have been conducted on the direct effect of DSS

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on SCP while ignoring the moderating variable of TMS. In the extant literature, TMS has been used as a moderating variable (Jayeola et al., 2022). Thus, based on these findings, it is revealed that top management support may be an important mediating factor affecting the relationship between KPI as a dimension of DCC and SCP. Osei et al. (2023) further suggested that TMS ensures the alignment of KPIs with organizational strategy and facilitates the allocation of resources. Leadership that emphasizes performance management and feedback mechanisms increases employee motivation and accountability, thus reinforcing SCP. Uddin and Akhter (2022) also argued that top management's commitment to transparency and communication is essential to developing a performance-based culture. On the other hand, Martínez-Peláez et al. (2023) suggested that top management support plays an important role in overcoming performance measurement resistance. Their findings show that strong leadership ensures that performance metrics are incorporated into the organizational strategic planning process, improving the overall effectiveness of KPIs in SCP implementation. These findings emphasize that TMS could be a moderating variable between TMS and SCP.

Further empirical evidence also shows that TMS could also moderated between CSFs and SCP. Senior leadership objectives to identify and address critical success factors are essential to successful supply chain management (Buzdugan & Capatana, 2021). Research indicated that TMS for collaborative support, investment in technology, and encouragement of process improvements significantly enhance SCP. Furthermore, Joel and Oguanobi (2024) also confirmed that top management's focus on strategic planning and continuous learning increases a culture of innovation and change. Leadership's active involvement in CSF management ensures that supply chain strategies are implemented effectively and in line with organizational objectives, leading to higher SCP (Sumant et al., 2024). Singh (2024) further suggested that leadership commitment to understanding customer needs and aligning supply chain strategies accordingly is critical to the success of SCP. This customer-centric approach ensures that supply chain strategies are not only efficient but also effective in meeting market demands. The following hypothesis is formulated based on the above hypothesis,

H4: Top Management Support Significantly Moderates Between KPIs and Supply Chain Performance.

H5: Top Management Support Significantly Moderates Between CSFs and Supply Chain Performance.

TMS also plays an important role in the impact of AI on SCP. Successfully integrating AI into supply chain operations requires strong leadership and strategic vision (Joel et al., 2024). This is further supported by the study of Uren and Edwards (2023) who suggested that a TMS facilitates the adoption of AI by providing essential elements that nurture a culture of innovation and ensure alignment with business objectives.

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Mokogwu et al. (2024) also highlighted the role of TMS in enhancing the testing and learning culture necessary for the successful implementation of AI technologies. Their study shows that leadership commitment to innovation and continuous improvement leads to better integration of AI in supply chain management, which increases SCP. Besides, Yu et al. (2023) also highlighted the importance of supporting top management in dealing with challenges associated with AI adoption, such as data privacy, ethical considerations, and business development and their research shows that leadership practices den ensures that these challenges are effectively addressed, and that organizations can take full advantage of the potential of AI to improve SCP. Thus, supporting the evidence of literature, study with moderating effect following hypothesis is formulated below,

H6: Top management support significantly moderates between ai and supply chain performance.

Methodology

The study objective was to test the impact of decision support systems (DSS), and artificial intelligence (AI) on supply chain performance (SCP) with the moderating effect of top management support systems (TMS) of dairy products manufacturers. Quantitative research approach was used to test the study hypothesis. This approach is considered to be more effective when data is collected through the survey instrument on Likert Scale (Cheung & Wang, 2017). After enforcing the significance of survey instrument, current study has utilized the data collection tool cross sectional survey instrument which was distributed among the dairy products manufacturing firms which were chosen due to their critical impact of their performance outcomes on consumer satisfaction. Operating in a highly uncertain environment where consumer awareness is steadily rising, these manufacturers must ensure their products meet diverse health-related expectations. Data collection targeted the employees of dairy products which are responsible for operational decisions. These individuals were selected for their comprehensive understanding of both the technical and conceptual dimensions of the surveys. A convenience sampling method was used in the data collection, with a final sample size of 400 participants. Convenient sample technique is considered to be effective when time and resources are limited to rigor the study (Etikan et al., 2016). Initially, potential informants were sent an invitation letter which is providing a description of the study and requesting their participation. 310 questionnaires were returned. In these responses, 300 responses were valid for further analysis. This final sample size fulfilled the requirements for complex data analysis and ensured that all reliable and generalizable factors were identified for the analysis (Christodoulou et al., 2015).

The survey instrument which was distributed among the respondents was adopted from the extant literature where it was already used and tested. Decision support

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system measured by two dimensions namely key performance indicators (KPI), critical success factors (CSFs). KPI comprises by five items, and CSFs also measured by five items. These items were taken from the study of Khiabani and Mahmoudian (2020). Supply chain performance (SCP) comprises by five items (Lee et al., 2022). Lastly, artificial intelligence measured by five items (Kumar et al., 2024). Lastly, top management system measured by 5 items which were adopted from the study of (Al-Husseini, 2024). These items were measured on a points Likert Scale where 1 was used for strongly disagree and 5 for strongly agree. As the structured instrument was utilized to gather the quantitative data using a drop and pick up method. The conceptual model's parameters were categorized into perceptual and operational items to ensure comprehensive coverage. A pre-test was conducted with a subset of informants to refine the questionnaire, control for variance, and verify the model's face validity. This rigorous approach ensured that the data collected was robust and suitable for subsequent analysis. Questionnaire items were first tested by an expert panel to ensure clarity and relevance, so they could be revised based on feedback followed by pilot testing with a group of participants small followed, all questionnaires had a Cronbach alpha value greater than 0.7, indicating strong internal consistency and reliability. The study variables are predicted in Figure 1

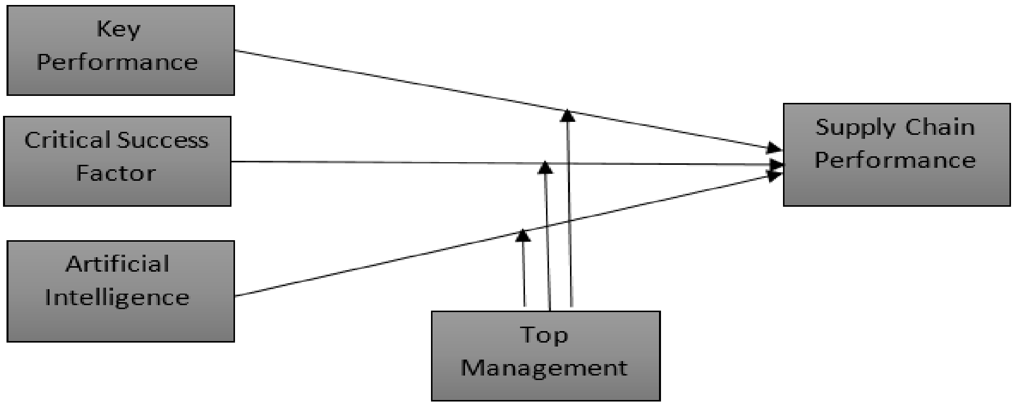

Figure 1: Conceptual Framework

Results

Both the demographic and inferential were conducted to test study objective which are predicted in next two sections. Both of SPSS and AMOS software's were used. Using AMOS Structural Equation Modeling (SEM) technique was employed.

Demographic Characteristics

Table 1 predicted values show the demographic characteristics of the study. The demographic data collected from 300 employees of a dairy products company presents a detailed profile of the workforce. In terms of gender distribution, 60% of the employees are male, and 40% are female, reflecting a relatively balanced gender representation within the company. Age-wise, the largest group of employees falls

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within the 26-35 years age bracket, comprising 33.3% of the total workforce. This is closely followed by the 18-25 years group, which accounts for 26.7% of the employees. The remaining age groups are represented in smaller proportions, with 20% in the 36-45 years range and 10% above the age of 45. Regarding educational qualifications, the majority of employees (60%) hold a Bachelor's degree, signifying a well-educated workforce with foundational academic qualifications. A smaller proportion of employees possess a Master's degree (16.7%), and 16.7% have only completed a High School diploma. These results indicate that the workforce is relatively highly educated, with a significant portion having completed tertiary education.

Table 1: Demographic Characteristics

Demographic Variable	Category	Frequency (N)	Percentage (%)
Gender	Male	180	60%
	Female	120	40%
Age Group	18-25 years	80	26.70%
	26-35 years	100	33.30%
	36-45 years	70	23.30%
	46-55 years	40	13.30%
	56+ years	10	3.30%
Education Level	High School	50	16.70%
	Bachelor's Degree	180	60%
	Master's Degree	50	16.70%
	PhD	20	6.70%
Work Experience (in years)	1-5 years	100	33.30%
	6-10 years	120	40%
	11-15 years	50	16.70%
	16+ years	30	10%
Job Role	Production Worker	120	40%
	Quality Control	80	26.70%
	Sales/Marketing	60	20%
	Administration	40	13.30%
Department	Manufacturing	150	50%
	Quality Assurance	70	23.30%
	Sales/Marketing	50	16.70%
	Administration	30	10%

Work experience within the company shows that 40% of employees have between 6 to 10 years of experience, suggesting a highly experienced workforce capable of contributing valuable industry insights. A significant 33.3% of employees have between 1 to 5 years of experience, pointing to a younger, more dynamic segment of the workforce, which could bring fresh ideas and energy. Only 26.7% have more than 10 years of experience, highlighting a smaller proportion of long-term employees

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within the company. In terms of job function, 50% of the workforce is involved in manufacturing, which is expected in a dairy products company, as it requires a large workforce to handle the production process. Quality assurance personnel make up 23.3% of the workforce, demonstrating a strong focus on maintaining the product's quality standards. Additionally, 16.7% of employees work in sales and marketing, indicating a dedicated team for promoting and selling the dairy products. Lastly, 10% of employees are engaged in administrative roles, ensuring smooth operations within the company. The above results are predicted in Table 1.

Reliability and Validity

This section of the paper represents reliability, convergent validity, and discriminant validity. In the outer loadings, factor loadings represent the correlation between observed variables and their underlying latent constructs which were analyzed to ensure each item exceeded the recommended threshold of 0.70 which is indicating strong item reliability (Cheung & Wang, 2017). Composite Reliability (CR) measures the overall internal consistency of the items in a construct that was evaluated and found to be satisfactory, along with Cronbach's Alpha (CA), confirming internal consistency (Vaske et al., 2017). The CR threshold value should be greater than 0.70. Convergent validity was assessed by calculating the Average Variance Extracted (AVE), which indicates the amount of variance captured by a construct relative to the amount due to measurement error. An AVE value above the threshold of 0.50 is considered satisfactory. Table 2 predicted values show that the construct fulfills the requirement of factor loadings, CR, and AVE which shows that construct has the convergent validity. The above results are predicted in Table 2.

Table 2: Convergent Validity

Construct	Item	Mean	Loading	AVE	Composite Reliability (CR)	Outer T-statistic
Top management support	TMS1	3.882	0.715	0.639	0.897	12.85
	TMS2	3.672	0.837			43.76
	TMS3	3.892	0.654			10.11
	TMS4	3.812	0.931			49.18
	TMS5	3.672	0.832			26.22
Key Performance Indicator (KPI)	KPI1	3.802	0.749	0.589	0.877	13.05
	KPI2	3.782	0.759			47.01
	KPI3	3.023	0.736			15.57
	KPI4	3.782	0.735			45.36
	KPI5	3.672	0.853			23.15

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Cont…

Construct	Item	Mean	Loading	AVE	Composite Reliability (CR)	Outer T-statistic
Critical Success Factor (CSF)	CSFs1	2.831	0.734	0.662	0.906	18.34
	CSFs2	4.932	0.838			44.91
	CSFs3	3.892	0.743			15.92
	CSFs4	3.782	0.901			41.76
	CSFs5	3.854	0.841			21.89
Supply chain performance	SCP1	3.692	0.735	0.650	0.902	7.71
	SCP2	3.842	0.823			63.44
	SCP3	3.672	0.832			24.77
	SCP4	3.212	0.762			8.6
	SCP5	3.982	0.872			17.85
Artificial Intelligence	AI1	4.892	0.872	0.703	0.921	16.45
	AI2	4.121	0.785			29.13
	AI3	4.121	0.766			9.11
	AI4	3.892	0.789			46.21
	AI5	3.892	0.981			24.83

Discriminant Validity

Discriminant validity in AMOS ensures that the constructs in the structural equation model (SEM) differ from each other. It examines the extent to which a construct is not significantly correlated with other constructs that differ from it theoretically. A common method for testing discriminant validity in AMOS is the Fornell-Larker criterion, in which the square root of each construct's average variance (AVE) is calculated where the square root of AVE's is larger than the correlations (Henseler et al., 2015). Another approach is the Heterotrait-Monotrait (HTMT) ratio, which indicates that a threshold of 0.85 or 0.90 indicates discrimination accuracy (Henseler et al., 2015). Ensuring discriminant validity is important because it emphasizes that the parameters used are inconsistent and that each parameter contributes uniquely to the explanatory power of the model (Hair Jr et al., 2020). Below Table 3 values show that the construct fulfills the requirement of discriminant validity through Fornell and Larker.

Table 3: Discriminant Validity

	VIF	AI	KPI	CSF	TMS	SCP
AI	1.345	0.799				
KPI	1.783	0.605	0.767			
CSF	1.383	0.323	0.515	0.814		
TMS		0.363	0.272	0.344	0.806	
SCP		0.282	0.269	0.241	0.323	0.838

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Model Fitness

The good fit indices indicate that the model exhibits a strong fit to the data. The chi-square/df value of 2.780 is well below the threshold of 3, indicating a good model fit. The RMSEA value of 0.003, which is much lower than the acceptable limit of 0.085, indicates a small error and a very good fit. A CFI value of 0.981 exceeds the threshold of 0.9, indicating a good fit, while a TLI value of 0.914, even above the 0.9 benchmark, indicates a good fit of the model and an NFI value of 0.933 above 0.9 confirms it tree for example describes the data well. Overall, these indices indicate that the model is a reliable representation of the data and a good fit. The above results are predicted in Table 4.

Table 4: Model Fitness

Index	Acceptable Range	Result
Chi-square/df	< 3	2.78
RMSEA	< 0.085	0.003
CFI	> 0.9	0.981
TLI	> 0.9	0.914
NFI	> 0.9	0.933

Regression Results

The SEM results show that Key Performance Indicators (KPIs) positively and significantly impact Supply Chain Performance (SCP) which supports hypothesis 1. This result indicates that well-defined KPIs are crucial for improving supply chain performance. Similarly, Critical Success Factors (CSFs) positively and significantly influence SCP, supporting hypothesis 2. These results highlight the importance of identifying and focusing on key factors that drive successful supply chain operations. Artificial Intelligence (AI) also has a positive and significant effect on SCP which is supporting to hypothesis 3. These results demonstrate AI's vital role in optimizing supply chain processes. Additionally, Top Management Support (TMS) significantly moderates the relationship between KPIs and SCP which supports hypothesis 4. This shows that management support enhances the positive impact of KPIs on supply chain performance. TMS also moderates the relationship between CSFs and SCP which supports hypothesis 5. The TMS also positively and significantly moderated between AI and SCP which supports the hypothesis 6. These results underline the significant role of KPIs, CSFs, AI, and TMS in enhancing supply chain performance. The above results are predicted in Table 5 and Figure 2 below,

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Table 5: Hypothesis Results

Hypothesis	Coefficient	Standard Error	t-Value	p-Value	Decision
KPIs -> SCP	0.251	0.065	3.861	0.001	Accepted
CSFs -> SCP	0.331	0.075	4.413	0.002	Accepted
AI -> SCP	0.354	0.086	4.116	0.000	Accepted
R Square Without a moderator	0.453				
TMS*KPIs -> SCP	0.272	0.079	3.443	0.000	Accepted
TMS*CSFs -> SCP	0.341	0.094	3.627	0.001	Accepted
TMS*AI -> SCP	0.382	0.089	4.292	0.000	Accepted
R Square With Moderator	0.562				

Note: KPIs-Key Performance Indicators, CSFs-Critical Success Factors, AI-Artificial Intelligence, TMS-Top Management Support, SCP-Supply Chain Performance

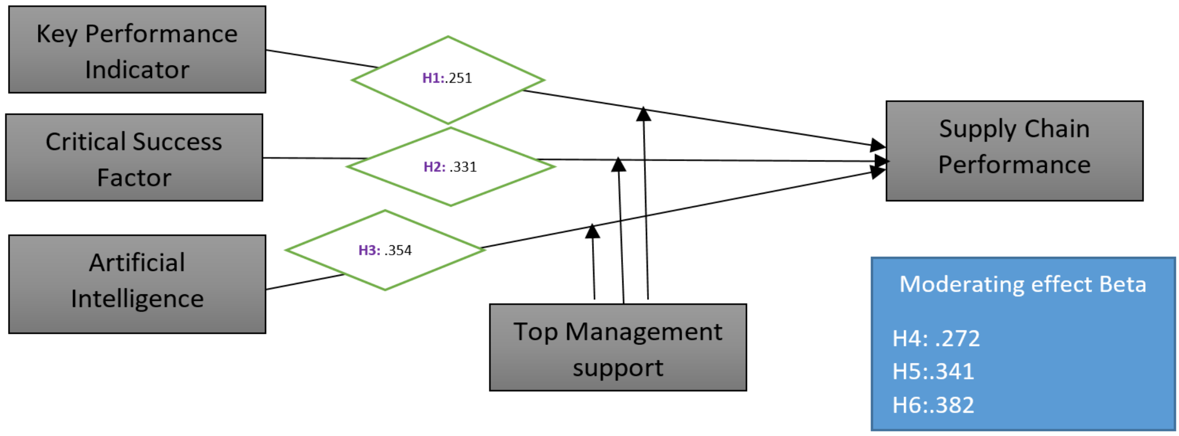

Figure 2: Beta values

Discussion

The study objective was to test the impact of decision support systems (DSS), and artificial intelligence (AI) on supply chain performance (SCP) with the moderating effect of top management support systems (TMS) of dairy products manufacturers. Overall, findings support the view that DSS and AI have been important factors in increasing the SCP. Similarly, TMS also positively and significantly moderated among DSS, AI, and SCP. In the separate dimensions of DSS, key performance indicators (KPIs) significantly and positively influence the SCP of dairy product manufacturers. This study's findings highlighted key KPIs' critical role in improving DSS to improve SCP performance. In particular, KPIs in dairy products are enabling organizations to better measure, monitor, and manage their supply chain activities. By focusing on critical areas such as order accuracy, lead time, and inventory turnover, organizations can gain deeper insights into their operational efficiency and inefficiencies, and consequently, this real-time analysis allows for rapid data identification and corrective measures. Additionally, consistent KPIs ensure that supply chain strategies align with organizational objectives and remain

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flexible to market changes. The result is supported by the literature (Gualandris et al., 2015; Kalf et al., 2023) where KPIs have been associated with performance and confirmed that organizations that use KPIs can achieve better operational efficiency and responsiveness, which is crucial to maintaining competitive advantage in dynamic industries such as the dairy industry. This evidence demonstrates that through systematically implementing KPIs, dairy producers can improve inventory efficiency, streamline processes, and increase overall performance.

Furthermore, critical success factors (CSF) as a dimension of DSS also positively and significantly influence to SCP of dairy product manufacturers. These results demonstrated that emphasizing CSF increases the importance of ensuring organizations focus on essential elements that drive success. In particular, CSF such as supplier collaboration, quality control, and customer engagement are critical to building a strong and resilient supply chain. These factors help organizations prioritize activities that are likely to have positive outcomes, ensuring that resources are directed to areas where they can have the greatest impact. These arguments and study findings are supported by the extant literature (Baah et al., 2022; Nguyen et al., 2022), where they supported the view and highlighted how focusing on CSF enables companies to achieve strategic alignment and operational excellence. This evidence demonstrated the evidence in the case of dairy products, that CSF is an important factor in increasing the SCP which in turn could lead to better communication with suppliers, better product development, and better customer service. As a result, this strategic focus enables the manufacturer to meet customer needs, reduce operating costs, and increase the overall supply chain efficiency of the dairy products manufacturers.

In addition, AI positively and significantly influences the SCP of dairy products manufacturing. This result demonstrated the view that AI has emerged as a transformative force in supply chain management with findings confirming a positive impact on SCP. In particular, AI technology facilitates dealing with big data roles, enabling predictive analytics and real-time decisions that improve various supply chain performances. As a result, integrating AI enables organizations to anticipate market trends, mitigate risks, and optimize supply chain management. This result highlights the view of the prior literature (Rashid et al., 2024), where they found that AI's ability to improve supply chain agility and flexibility is essential to sustain competitiveness in fast-moving industries. Generally, these outcomes supported the view that for dairy producers, the adoption of AI could lead to significant improvements in production planning, inventory management, and distribution efficiency. Eventually, by using AI, manufacturers can reduce waste, increase product efficiency, and improve lead times, all of which contribute to the availability of more efficient and cost-effective supply chains which will increase the productivity and competitive advantage of dairy manufacturing companies.

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On the other hand, TMS also positively and significantly moderates between DSS dimensions (KPI, CSF) and SCP of dairy products manufacturing companies. These findings supported the view that TMS plays an important role in the relationship between DSS dimensions and SCP. In particular, TMS ensures that the resources, strategic vision, and organizational commitment are in place to enhance performance measurement systems and processes. Without strong leadership, the implementation of KPIs and CSFs may not be the contribution needed to drive meaningful change. This argument is supported by Jayeola et al. (2022) who emphasized the importance of increasing a culture of TMS accountability and continuous improvement, which is essential to sustaining long-term success. Commonly, these results supported the view that the active involvement of government officials in supporting supply chain strategies for dairy producers ensures that performance specifications are not only followed but that they work to provide order improvements and innovations. Consequently, this leadership support can facilitate a faster and more efficient supply chain to meet the challenges of the dairy industry can increase the acceptability of dairy products in the international market.

In the last findings, TMS also positively and significantly moderates the relationship between AI and SCP of dairy manufacturing products. These results highlighted the importance of leadership in technology adoption and innovation. Specifically, TMS provides strategic direction to provide the necessary work and support to overcome resistance to change and ensure successful AI integration. This argument is supported by the findings of Mokogwu et al. (2024) who also argued that leadership plays an important role in creating a culture that embraces technological advancement and continuous learning. This finding confirms the importance of TMS because a strong TMS for dairy producers can help accelerate the adoption of AI technology, for efficiency, better risk management, and improved decision-making that can increase their supply chain speed, responsiveness, and overall performance build. As the moderating effect of the top management support system has been tested first time, therefore directly this relationship could not be supported but these findings could be supported by other findings where TMS has been used moderating variable (Jayeola et al., 2022; Zhao et al., 2024). These findings indicated that TMS also strengthens the relationship of DSS, AI, and SCP in dairy products manufacturing firms which shows showing the moderating effect is a major contribution of the study.

Implication

This study provides important theoretical implications through the joint impact of DSS and AI on SCP which is contributing to a broader understanding of how advanced technology could improve supply chain management. Unlike previous studies that examined DSS and AI separately, this study combines components into a framework that shows that both DSS and AI have positive and significant impacts on SCP. Furthermore, this study addresses inconsistencies in previous findings by reaffirming the positive and

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significant effects of DSS and AI on SCP in a new context, thus providing a theoretical basis for the supply chain study is great. The inclusion of top management support (TMS) as a moderating variable further enhances the design, suggesting that strategic leadership is important for the successful implementation of AI and DSS technologies. TMS ensures that this technology is seamlessly integrated into business processes, maximizing its impact on SCP. This study shifts the focus from overall enterprise performance to specific supply chain outcomes, providing valuable theoretical insights into how organizations can use DSS, AI, and TMS to achieve competitive advantage in supply chain management. The study also explores the new evidence for the researchers to conduct their research that could increase new research areas for further research.

This study provides important practical implications for dairy producers seeking to enhance the performance of their supply chains through advanced technology. By combining decision support systems (DSS) and artificial intelligence (AI), dairy producers can achieve accurate demand forecasts, improve inventory management, and provide simplified outsourcing, improving efficiency and reducing costs. Findings show that DSS and AI jointly benefit from better information of the conducted decision which is essential in a highly competitive and perishable industry such as dairy Further, the role of TMS is emphasized which is emphasized as the key to successful implementation of this technology. Therefore, the dairy producers, strategic leadership is essential to ensure that AI and DSS are successfully integrated into an organization's supply chain strategy, encouraging innovation and agility. This approach enhances productivity and competitive advantage by enabling producers to respond more quickly to market changes, maintain product quality, and better meet customer needs, which could strengthen their market position and long-term sustainability.

Limitations and Future Direction

With the significant contributions of the research, the study has various limitations which opens a new avenue for further research. First, focusing on dairy producers may limit the generalizability of the findings to other industries with different supply chains. Future research could examine the effects of DSS, AI, and TMS in different areas to confirm and extend these findings. Furthermore, although this study highlights the positive moderating effect of TMS, it does not investigate into the details of specific management practices or organizational cultures that may further enhance technology integration. Future research could examine these aspects to provide more strong insights into the role of leadership in technology adoption. Finally, the study is limited to cross-sectional research design, future research could be explored on longitudinal research design to know the variations in results.

Conclusion

The study objective was to test the impact of decision support systems (DSS), and artificial intelligence (AI) on supply chain performance (SCP) with the moderating effect of top

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management support systems (TMS) of dairy products manufacturers. The findings emphasized the critical influence of DSS and AI in enhancing SCP which is highlighting the synergistic benefits of integrating these technologies for operational efficiency, risk management, and strategic decision-making. Key performance indicators (KPIs) in DSSS were shown to significantly enhance SCP by enabling organizations to measure, monitor, and manage supply chain activities effectively. This includes improving order accuracy, reducing lead times, and optimizing inventory turnover which are contributed to increase SCP. The role of critical success factors (CSF) was also significantly increasing the SCP through the supplier collaboration, quality control, and customer engagement which is ensuring a resilient and responsive supply chain.

The study further revealed that AI positively impacts SCP through facilitating big data analysis, predictive analytics, and real-time decision-making, which enhances supply chain agility and flexibility. The integration of AI allows organizations to anticipate market trends, mitigate risks, and optimize operations, leading to improved production planning, inventory management, and distribution efficiency. Other findings shown that TMS emerged as a significant moderator in the relationship between DSS, AI, and SCP which is emphasizing the necessity of strategic leadership for the successful implementation of advanced technologies. TMS ensures resource allocation, strategic vision, and organizational commitment, which are crucial for the continuous integration of DSS and AI into business processes. The study with these findings contributes the novel insights with the combined effects of DSS and AI on SCP which is highlighting the importance of TMS as a moderating factor, and offering practical implications for dairy producers to enhance their SCP.

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Appendix: Questionnaire

Indicator	Description
key performance indicators	We want to achieve the desired profit level
	We want to achieve the desired sales level
	We want to achieve the desired market share
	We want to evaluate the overall performance / We want to evaluate the market capacity
	We want to achieve market competitive advantage.
critical success factors	We want to achieve a high level decision support system with key marketing performance indicators
	We want to achieve an automated reporting of performance from a full range of marketing activities
	We want to evaluate performance information for individual marketing programs
	We want to achieve decentralized decision-making authority
	We want to achieve each person as a whole for decision making in the business unit
Supply chain performance	Improve sales.
	Improve order fill rate.
	Improve manufacturing lead time.
	Improve the quality of the product.
	Improve reliability on supply chain delivery including lower shipping errors
Top Management support	In our research centre, top management thinks that encouraging knowledge acquisition and sharing among academics and researchers is beneficial.
	In our research centre, top management always supports academics and researchers to acquire and share knowledge with each other.
	In our research centre, top management provides most of the necessary help to enable academics to acquire and share knowledge.
	In our research centre, top management is keen to see that academics and researchers are happy to share knowledge with each other.
	Top management supports the research centre's work by providing resources.
	Top management supports the work of the research centre.
Artificial intelligence	Is data analytics help AI adoption in manufacturing?
	Is AI technology help financial planning in Manufacutring?
	Is AI technology influence business innovation in manufacturing?
	Respond to competitor strategy Is AI technology helping in quick response to the competitors of manufacturing?
	Is data analytics help AI adoption in manufacturing?