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Artificial Intelligence-enabled Decision Support Systems for Supply Chain Management in Pharmaceutical Industry

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Abstract

Artificial intelligence (AI) has become a potent instrument that utilizes personal knowledge and offers quicker fixes for difficult problems. Promising developments in artificial intelligence and machine learning offer a game-changing prospect for drug discovery, formulation, and dosage form testing. Through the application of AI algorithms that examine vast amounts of biological data, such as proteomics and genomics, scientists are able to pinpoint targets linked to disease and anticipate how those targets may interact with possible therapeutic candidates. This makes it possible to approach drug discovery in a more effective and focused manner, which raises the possibility of successful drug approvals. Additionally, by streamlining research and development procedures, AI can help lower development costs. Pharmacokinetics and toxicity of potential drugs can be predicted using machine learning algorithms, which also help with experimental design. This capacity lessens the need for extensive and expensive animal research by enabling the prioritization and optimization of lead compounds. Artificial intelligence (AI) algorithms that evaluate real-world patient data can support personalized medicine strategies, improving patient adherence and treatment outcomes. The current study examines the implications of artificial intelligence (AI), supply chain dynamism and unpredictability, and supply chain resilience (SCP), both directly and indirectly. As a result, we have based our conceptualization of AI's use in supply chains on the theory of organizational information processing (OIPT). The framework that was established was assessed using the application of structural equation modeling (SEM). Survey information was gathered from 150 businesses of all sizes, operating in different nations and industries.

Keywords: *Artifical Intelligence, Frug Discovery, Machine Learning, Pharmacokinetics, Personalized Medicine, Supply Chain Dynamism*

1. INTRODUCTION

As a vital sector, the pharmaceutical business depends on ongoing innovation and the adoption of new technology to meet the problems facing global healthcare and react to medical catastrophes, like the most recent pandemic [1]. Small pharmacological compounds and biologics are among the innovations, with improved stability and high potency being preferred. But there are a lot of challenges facing the sector that call for more technologically advanced solutions[2]. The healthcare industry has a continuing need for skilled workers, which makes it necessary to detect skill shortages and provide ongoing training [3-6]. Disruptions to the supply chain have become the second most difficult obstacle to overcome, and a number of pharmaceutical companies are looking forward to new developments in their supply chains and creative business models to boost resilience [4-8].

Supply chain disruptions are made worse by pandemics, natural catastrophes, price adjustments, cyberattacks, delays in logistics, and problems with products [9-11]. The pharmaceutical business faces a number of difficulties, including transportation issues, decision-induced delays for supplier pricing updates, cross-border trade cooperation tactics, an increase in criminal activity, and unstable resource availability. Many COVID-19 vaccinations were rendered useless during the pandemic because of issues with maintaining the cold chain. Disruptions to the pharmaceutical supply chain can have a substantial impact on prospective earnings, corporate reputation, and consumer happiness . Artificial Intelligence (AI) has the potential to revolutionize the pharmaceutical industry's supply chain operations by combining several AI research projects to develop practical solutions for a range of supply chain problems.

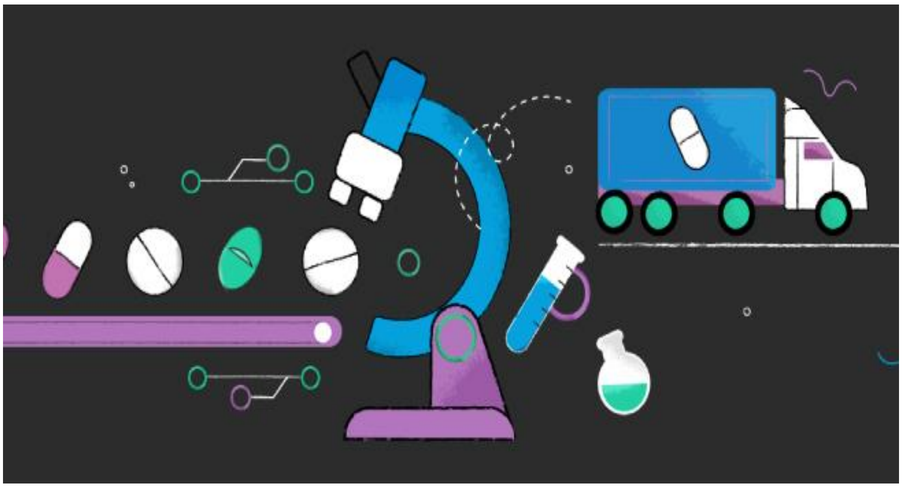

Figure 1: AI in Drug Supply Chain Management

2. LITERATURE REVIEW

Andronie et al. (2021)[12] investigated the incorporation of deep learning, Internet of Things (IoT) sensing networks, and artificial intelligence (AI) in cyber-physical production systems (CPPS). The authors stressed the value of AI-based decision-making algorithms in CPPS optimization, including everything from resource allocation to production scheduling. They talked on how real-time data acquisition from various production environment components was made possible by IoT sensing networks, allowing for improved monitoring and control. The assessment also emphasized how deep learning helps smart process management by evaluating vast amounts of data to derive insightful conclusions and enhance system functionality. The next generation of smart manufacturing systems will be made possible by the integration of AI, IoT, and deep learning technologies, which have the revolutionary potential to improve the efficiency, flexibility, and adaptability of CPPS. This has been highlighted through the synthesis of existing literature.

Barnes and Zvarikova (2021) [13] examined the potential uses of Internet of Things (IoT)-based healthcare apps, clinical and diagnostic decision support systems, and wearable medical devices with AI capabilities for COVID-19 prevention, screening, and treatment. The authors looked at how these technologies have been used to improve patient care in a number of ways during the pandemic, such as early symptom detection, remote vital sign monitoring, and individualized treatment recommendations. The study also looked at how AI algorithms may be used to evaluate massive datasets produced by IoT sensors and wearable technology, enabling risk assessment and predictive modeling for improved COVID-19 case management. Give light on the important ways that wearables, wearable AI, and Internet of Things (IoT) technology might enhance healthcare practices by a thorough evaluation of the literature that has already been published. This is especially important when it comes to addressing the COVID-19 pandemic that is currently threatening global health.

Samadhiya et al. [14] examined how supply network dynamic is affected by artificial intelligence (AI) methods for managing disruptions in supply chains. The authors looked at how supply chains' ability to bounce back and adapt to shocks has been affected by AI-driven methods, taking into account variables like volatility, uncertainty, complexity, and ambiguity (VUCA). They aimed to determine the degree to which supply chain dynamism influences the efficacy of AI-based disruption management solutions using empirical analysis and modeling. In order to offer practitioners and decision-makers insights into the relationship between AI approaches and supply chain dynamics and implications for improving the resilience of their supply chain operations in challenging circumstances, a variety of scenarios and case studies were analyzed.

Knop et al. (2022) [15] investigated the variables affecting the way doctors and artificial intelligence (AI)-enabled clinical decision support systems (CDSS) interact. The study concentrated on how healthcare workers interact with AI-based technologies in clinical settings, taking into account both technological and human variables. The authors examined user experience, interface design, cognitive effort, trust, and perceived usefulness of AI-driven CDSS through a thorough examination of the body of existing literature. They also looked into how technological aspects like system correctness, transparency, interpretability, and interaction with current workflows affect medical practitioners' acceptance and uptake of AI solutions. The useful insights into the intricate interaction between technology characteristics and human factors that affect the efficient application of AI-enabled CDSS in healthcare delivery were obtained by combining findings from numerous studies.

3. RESEARCH METHODOLOGY

3.1 Instrument development

A survey-based tool was utilized to gather data for a cross-sectional study design. According to the study's context and pre-test findings, established measures from the literature were included into compliance recommendations with minor phrasing changes. A five-point Likert scale, with extreme points spanning from 1 = strongly disagree to 5 = strongly agree, was used to design the measuring items. Additionally, the SCP-related subjective metrics that are frequently employed in supply chain studies have been incorporated. In order to identify any flaws, nine supply chain specialists from various industries were asked to complete the questionnaire in the researcher's presence as a pre-test for face validity. Subsequently, the experts were requested to offer their general opinions on the design and applicability of the metrics employed in the construct evaluation process. The "Appendix" displays the

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measurement items and literature sources used to create the constructs. Every concept was used in a reflective manner.

3.2 Sampling design and data collection

International supply chains undergoing digital transformation through the application of AI techniques provide the empirical context for the research. The focal firm, from which one important respondent was approached to express his opinion of the study's constructs, served as the study's unit of analysis. The instrument was therefore created with a single respondent in mind. Additionally, 1120 possible responders—including managers and senior executives—were found in Maharashtra-based digitalized businesses. The involvement of the important respondents in the supply chain's adoption of AI has received particular emphasis. The important respondents were then sent an email with the survey. a questionnaire accompanied by a cover letter outlining the purpose of the research, potential uses for the data gathered, and a rigorous assurance of data confidentiality.

Table 1: Respondent Profile Analysis

Parameters	Details	Frequency	Percentage
Profile of Respondents			
Gender	Male	99	66
	Female	51	34
Department Profile	General Manager	45	30
	Unit Head	15	10
	Supply Chain Excutive /manager	60	40
	Operations Executive/ Manager	16	10.66
	Sales executive/manager	14	9.33
Managerial Experience	Between 5-6 years	49	32.66
	6-10	17	11.33
	10-15	57	38
	Above 15 years	27	18

The data presents insights into the profile of respondents and their characteristics within a professional context. In terms of gender distribution, the majority of respondents were male, comprising 66% of the sample, while females accounted for 34%. This gender imbalance reflects a common trend in certain industries or managerial roles. Regarding department profiles, the largest proportion of respondents held positions as supply chain executives or managers, constituting 40% of the sample, followed by general managers at 30%, unit heads at 10%, operations executives or managers at 10.66%, and sales executives or managers at 9.33%. This distribution indicates a diverse representation across different functional areas within the organization, highlighting the multidisciplinary nature of the study's scope. Furthermore, when considering managerial experience, the data reveals a varied distribution among respondents. The majority reported having managerial experience between 10-15 years (38%), followed by those with experience above 15 years (18%), between 5-6 years (32.66%), and 6-10 years (11.33%). This suggests a relatively experienced cohort of professionals

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participating in the study, with a significant portion having substantial tenure in managerial roles, which could influence their perspectives and decision-making processes within their respective domains. Overall, these findings provide valuable insights into the demographics and professional backgrounds of the respondents, offering a contextual understanding of the study's target population.

4. DATA ANALYSIS AND INTERPRETATION

Table 2: Mean Scores Analysis

Items	Mean	SD	Standardized Loadings	T-value
AI-1	3.70	1.14	0.870	14.5
AI2	4.40	1.20	0.760	12.1
AI3	4.45	0.50	0.880	13.5
AI4	4.3	1.51	0.810	11.30
AI5	4.50	1.80	0.830	11.14
AC1	4.01	1.7	0.715	11.7
AC2	4.45	2.01	0.807	11.70
AC3	2.65	0.75	0.860	12.95
SCC-1	2.51	1.45	0.880	13.30
SCC-2	2.80	1.50	0.701	13.40
SCC-3	3.0	2.04	0.800	11.75
SCC-4	3.01	0.50	0.697	12.7

The data provides insights into respondents' perceptions of artificial intelligence (AI), automation capability (AC), and supply chain complexity (SCC). Mean scores ranged from 3.70 to 4.50, indicating a favourable perception of AI technologies. Automation capability items received high ratings, with mean scores ranging from 4.01 to 4.45, indicating a positive perception of organizational automation capabilities. However, standard deviations were higher for some AC items, indicating greater variability in responses. Supply chain complexity items had mean scores from 2.51 to 3.01, suggesting a moderate perception of complexity among respondents. Standardized loadings were generally high for SCC items, indicating a strong association with the construct. T-values were consistently high across all items, indicating statistically significant relationships between the items and their respective constructs. Overall, respondents perceive AI technologies and automation capabilities favourably, acknowledging the moderate level of complexity within their supply chains.

Table 3: Construct Correlation Analysis

		CR	AVE	AI	AC	SCC
AI	0.880	0.965	0.680	**(0.825)**		
AC	0.80	0.895	0.674	0.356	**(0.805)**	
SCC	0.849	0.830	0.805	0.375	0.32	**(0.804)**

The data presented in this text presents the results of a confirmatory factor analysis, focusing on the correlations between three constructs: artificial intelligence (AI), automation capability (AC), and supply chain complexity (SCC). The construct reliability (CR) values for AI, AC, and SCC are above 0.8, indicating high reliability and consistency in their measurement. The average variance extracted (AVE) values for AI, AC, and SCC are well above 0.5, indicating adequate representation by their respective items. The diagonal values represent the square roots of AVE for each construct, providing insights into the proportion of variance explained by the underlying latent construct. The off-diagonal values indicate the degree of association between constructs, with a moderate positive relationship between AI and AC and a stronger positive relationship between AI and SCC. The data suggests high reliability and validity of the measurement model, offering valuable insights into the interrelationships between these key organizational constructs.

5. CONCLUSION

First off, the study's varied sample composition—mostly men with a range of executive positions and experience levels—ensures a thorough grasp of perspectives and encounters pertaining to the study's premises. Second, the respondents' positive opinions of artificial intelligence (AI) technologies suggest that enterprises are open to implementing and adopting AI as they see its potential advantages. In addition, businesses believe they have significant automation capabilities, which is consistent with supply chain management's growing digitalization trend. The acknowledgement of supply chain complexity is modest, indicating a comprehension of the difficulties in managing intricate supply networks in the context of digital transformation and artificial intelligence implementation. The results of the confirmatory factor analysis demonstrate the complex relationships that exist between organizational capacities, supply chain management, and technology innovation. Specifically, the results show a strong positive link between supply chain complexity, AI, and automation competence. These results underline the significance of comprehending the intricate linkages between supply chain complexity, automation capability, and AI adoption. They have implications for both research and practice. Businesses can use these insights to guide resource allocation and strategic decision-making, with an emphasis on improving automation capabilities and successfully handling supply chain complexity in the digital age. In summary, the research adds significant knowledge to the body of literature regarding the integration of artificial intelligence and digital transformation in supply chain management. It provides a sophisticated comprehension of the attitudes, obstacles, and connections between important organizational components .

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