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Artificial Intelligence Applications for Responsive Healthcare Supply Chains: A Decision-Making Framework

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Artificial Intelligence Applications for Responsive Healthcare Supply Chains: A Decision-Making Framework

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Abstract: Post-Covid-19, the healthcare sector is extensively digitalizing operations by applying emerging technologies such as Artificial Intelligence (AI). It is evident from previous research that the adoption of AI in the healthcare supply chain results in unmatched benefits. Therefore, the present study identifies the enablers for adopting AI in healthcare supply chains and validates them using the Fuzzy-Delphi technique. Furthermore, enablers are prioritized and the dyadic connections between them were investigated using the Fuzzy-DEMATEL approach. In the last phase, the Graph Theory Matrix Approach was applied to assess the readiness of a case organization to adopt AI across various healthcare functions. The sensitivity analysis confirms the reliability of the results. Competitive and mimetic pressures, together with government policies and support, were the most influencing enablers. Furthermore, Scalability and Traceability of information flow across healthcare supply chain is found to be the most influenced factor by other enablers.

Keywords: Artificial intelligence (AI), Healthcare Supply chain management (HSCM), Enablers, Responsiveness, Fuzzy-Delphi, Fuzzy-DEMATEL, Graph Theory Matrix Approach (GTMA).

1. Introduction

Post Covid, healthcare sector is under huge pressure to make its operations more resilient and cost effective to serve society in an effective manner (Vishwakarma et al., 2023). Healthcare supply chain management (HSCM) is directly linked with people's health. Therefore, it needs to be given utmost importance by all stakeholders (Bag et al., 2021; Kumar et al., 2023a). Technology and innovations play a crucial role in making supply chains flexible, agile, and responsive (Rajan and Dhir, 2023). Among emerging technologies, AI has massive potential

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for transformation of operations (Brem et al., 2021). Advancements in technologies lead to seamless customer experience by offering real-time information and profit maximization for organizations (Chang et al., 2023).

In healthcare sector, AI-based algorithms may be beneficial for precisely predicting medical items requirements and minimizing the inventory holding and obsolescence cost. Moreover, AI is beneficial to overcome counterfeiting issues. AI can help medical professionals assess the prospective demands of required products and services so that the same can be arranged without any delays. Siala & Wang (2022) mentioned that it is challenging to create AI-based systems that are foolproof and in compliance with ethics and standards. The authors further mentioned that it requires significant funds, a focus on data governance, and advanced algorithms. Furthermore, Trocin et al. (2021) discussed that responsible AI ensures transparent, unbiased, and indiscriminate results.

Since AI-based systems work on programming using black-box, patients might be scared whether they are getting the right treatment or not. Therefore, patients may be resistant to give consent for AI systems-based treatment (Cohen et al., 2014). Many times, medical practitioners also do not know how AI is coming to a decision, which can be worrisome. AI adoption in HSCM is discussed to have incomparable benefits across various supply chain linkages (Gupta et al., 2021). However, its adoption is highly challenging and complex, as discussed in academic literature published to date. In a study conducted by Deloitte (2022), it was found that top management commitment and strategic planning were the key success factors for adopting AI in HSCM. HSCM primarily deals with identifying and utilizing resources for effectively controlling and managing healthcare services to ensure the welfare of patients. Moreover, it has been also observed that AI in healthcare is a highly emerging area in in context to India also (STPI, 2022).

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India has crossed a population of 1.42 billion, ranked first worldwide. With the increasing population, it is urgently required to enhance medical facilities for public welfare. India's healthcare system is often complex and dominated by public and private players (Kumar, 2023). Due to the demand-supply gap, some loopholes include scarcity of required infrastructure facilities, shortage of dexterous doctors and staff, lack of funds, and lack of advanced healthcare facilities. Furthermore, as per Geetika et al. (2023), there is an urgent need for radical innovations in healthcare services to provide effective healthcare services to the vast population of India, the majority of which live in rural areas.

India has already started Ayushman Bharat Digital Mission, under which more than 550 million persons get medical coverage of five lakhs for secondary and tertiary treatments (Geetika et al., 2023). Also, e-health market size in India is expected to attain a value of US $10.6 million by 2025 (IBEF, 2023). Moreover, there is a crucial need for adopting emerging technologies to enhance healthcare supply performance. Adopting AI in HSCM helps medical professionals to accurately diagnose the disease on time, so that the right medical treatment can be provided before the condition of the patient turns worse (Stewart, 2023). All countries across the globe are putting substantial efforts into adopting AI in HSCM. After careful literature review analysis, it is concluded that only a few studies are available in the context of a developing economy (Bag et al., 2023). Therefore, the research objectives of this study are proposed as follows:

i. To explore enablers for adopting AI in HSCM.
ii. To establish causal relationships among identified enablers so that AI can be successfully adopted in HSCM.
iii. To develop a mathematical model which can serve as a benchmark for assessing an organization's readiness for adopting AI in HSCM.

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The remaining section of the paper is as follows: Section 2 presents the theoretical development and exploration of enablers for AI adoption in HSCM. Section 3 explains the research methodology. Section 4 discusses the results involved and the decision framework for the case organization. The next section presents a discussion about the results. The penultimate section discusses theoretical and managerial implications. Finally, the conclusion and the scope for future work are presented. Findings will contribute to better understand the key enablers, assessing their relative importance, and developing strategies to adopt AI in HSCM successfully.

2. Literature review

2.1 Technology, Organization, and Environment (TOE) and Behavioral Aspects

TOE framework helps to elucidate the creative abilities of the firm to produce quality goods and deliver services in uncertain environments (Dwivedi et al., 2021). Introduced by Tornatzky & Fleischer (1990), the TOE framework can analyze a list of attributes to determine the probable chances for adopting technological innovations. Examining technological aspects through viability and feasibility analysis provides inputs to implement technology successfully. Moreover, focusing on technological aspects helps organizations gain a competitive edge and perform better (Kumar et al., 2023b). Organizational perspectives are equally crucial in adopting AI in HSCM. It includes the possessions and various initiatives taken by the organization. Strategic initiatives toward adopting digital technologies and innovative practices help organizations achieve competitive advantage (Chittipaka et al., 2023).

Moreover, environmental factors, including government policies, rules and regulations, and market pressure, impact AI adoption in HSCM (Raj & Jeyaraj, 2023). Focus on stringent cybersecurity norms can facilitate AI adoption in HSCM as the healthcare organization will feel safe and secure. In scholarly literature, TOE is used in a variety of applications, including

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Blockchain for supply chain (Chittipaka et al., 2023), Industry 4.0 adoption (Raj & Jeyaraj, 2023), smarter construction (Xue et al., 2023).

2.2 Enablers of AI adoption in Healthcare Supply Chain Management (HSCM)

Since adopting AI in HSCM requires a complete overhauling of operations, proper change management strategies are required for its successful adoption. Lack of change management and ineffective ways may negatively impact employees (Attaran, 2020). Moreover, the authors emphasized that employees must have advanced coding skillsets and be trained to understand the working rules and regulations while dealing with digital technologies. Büyüközkan et al. (2021) discussed the implications of having a decentralized system because of blockchain adoption, which further helps to enhance trust across supply chain linkages. Wei et al. (2020) investigated the role of top management commitment in developing a positive belief in adopting digital technologies. Moreover, the authors stated that adopting digital technologies required substantial funds and considerable transition time.

Effective strategies must formulate various business operations across stakeholders, resulting in effective coordination and cooperation. Toorajipour et al. (2021) discussed that various AI techniques used in the supply chain are genetic algorithms (GA), agent-based systems (ABS), and Artificial Neural Networks (ANN). Moreover, Kumar et al. (2023) discussed that a positive organizational culture facilitates a strong bond between managers and lower-level management, thereby enhancing learning and growth opportunities.

It is equally important that employees must be passionate, dedicated and motivated to learn new tools and methodologies to adopt AI in HSCM. Devi et al. (2024) discussed that focusing on human-centered design helps to bring creativity, innovation, encouragement, and engagement of humans for effective supply chain management. Cross-functional teams from diversified backgrounds help to equip the teams with various skill sets and quickly solve the identified problems.

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Kumar et al. (2023) highlighted the importance of scalable and sustainable technologies to overcome the anticipated risks. Moreover, Musamih et al. (2021) mentioned the role of traceability, scalability, and interoperability for effective HSCM adoption. Bas et al. (2023) discussed that the data used for training and testing must be reliable and error-free to get accurate results; otherwise, it may lead to biased results. Kumar et al. (2023) stated that government policies play a vital role in AI adoption in HSCM by providing necessary technical guidance and supporting infrastructure. Moreover, competitive and mimetic pressure urges organizations to think differently for the upliftment and increased healthcare supply chain performance.

3 Research Methodology

The research methodology consists of the following three phases. In the first phase, the fuzzy-Delphi technique was applied, which resulted in the shortlisting of twenty enablers; three were eliminated. In the second phase, the fuzzy-DEMATEL technique examines the causal relationship among enablers. Fuzzy-DEMATEL is a well-adopted technique for variable assessment and solving ambiguous and complex business problems (Feng & Ma, 2020). Eventually, in the third phase, the Graph Theory Matrix Approach (GTMA) was used to analyze organization readiness and compute comprehensive AI-HSCM index to examine the relative importance of distinct enablers. Research methodology is depicted in Figure 1.

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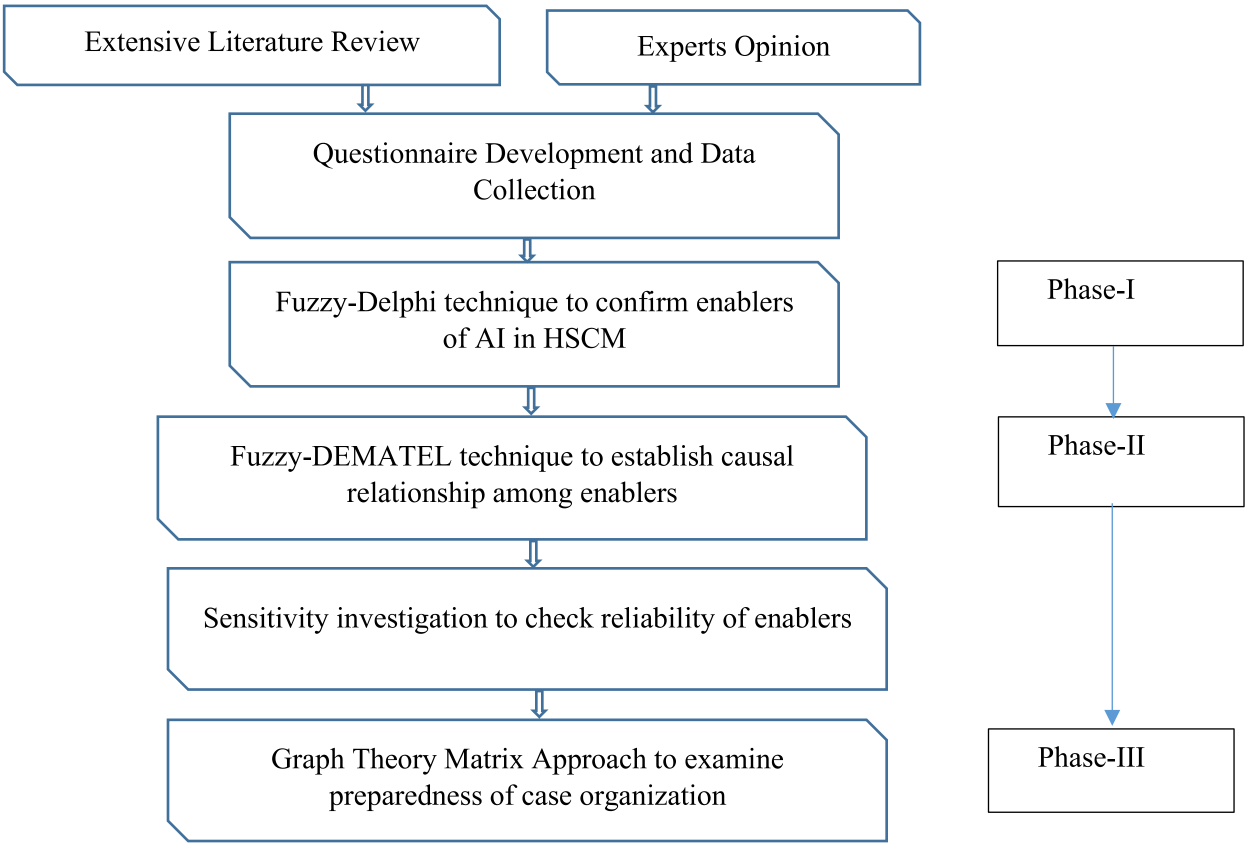

Figure 1: Research Methodology

3.1 Fuzzy-Delphi Technique

Dalkey and Helmer (1963) initiated Delphi technique to ensure consistency between respondents' answers. As many times, applying Delphi technique is time-consuming and cumbersome, fuzzy-Delphi technique is used to tackle these issues. The steps used in Fuzzy Delphi technique are as follows:

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Step 1: Identifying area experts and Variables in the study

Variables are identified using an extensive literature review and are confirmed with ten area experts. The area experts are chosen depending on their field of expertise and relevant experience.

Step 2: Development of Survey Instrument

The questionnaire was designed using extensive literature review. The utmost care was taken to develop the questionnaire so that respondents feel comfortable while understanding and answering to the questions. The experts were asked to provide their opinions on the enablers of AI in HSCM. The average experience of the area experts was 16.25 years. The eligible criterion was sufficient knowledge of AI and ten years working experience in healthcare supply chain management.

Step 3: Data collection and Analysis

In the beginning of the data collection process, the research objectives were discussed precisely with the area experts. Data was collected using triangular fuzzy number (TFN) scale as mentioned in Table 1. Let number of experts be P which were consulted to collect the responses. The experts investigated m enablers using fuzzy scale.

Table 1: Triangular Fuzzy Number Evaluation Scale (Akyuz & Celik, 2015)

Linguistic Term	**Triangular Fuzzy Number**
Not Important (NI)	(0,0,0.25)
Very Less Important (VLI)	(0,0.25,0.5)
Less Important (LI)	(0.25,0.5,0.75)
Highly Important (HI)	(0.5,0.75,1)
Very High Important (VHI)	(0.75,1,1)

Step 4: Converting Expert Scores into TFN

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Suppose $\tilde{w}_{ij}$ be triangular fuzzy number, which have minimum value as (a_{ij}), most likely value (b_{ij}) and maximum value (c_{ij}). The fuzzy weight, $\tilde{w}_j$ of jth enabler can be computed as follows:

$$\tilde{w}_j = (\alpha_j, \gamma_j, \beta_j) \quad \forall\, \mathrm{j} \in \mathrm{m}$$

Where

$$\alpha_j = \min_{i \in P} \left\{ a_{ij} \right\} \quad \forall j \in m \tag{1}$$

$$\gamma_j = \left\{ \prod_{i=1}^{P} b_{ij} \right\}^{1/P} \quad \forall j \in m \tag{2}$$

$$\beta_j = \max_{i \in P} \left\{ c_{ij} \right\} \quad \forall j \in m \tag{3}$$

Step 5: Defuzzification of fuzzy numbers

Using center of gravity method, the fuzzy weight value of j^{th} enabler, $\tilde{w}_j$ is computed as single value as Q_j and is given by equation (4) as mentioned below

$$Q_j = \frac{(\alpha_j + \beta_j + \gamma_j)}{3} \qquad \forall j \in m \tag{4}$$

Step 6: Selection of Enablers

For selection of enablers, threshold value δ is computed as

$$\delta = \frac{1}{m} \sum_{j}^{m} Q_j \tag{5}$$

$$\begin{aligned} &\textit{If } \; Q_j \geq \delta, \; \textit{the enabler is selected} \\ &Q_j < \delta, \; \textit{the enabler is rejected} \end{aligned}$$

3.2 Fuzzy-DEMATEL Technique

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Fuzzy-Decision Making Trial and Evaluation Laboratory (F-DEMATEL) was used to develop causal relationship among the identified enablers. The study also suggests the relative importance of enablers using quantitative approach (Feng & Ma, 2020). The purpose of using fuzzy technique was to eliminate the vagueness among the experts' opinions. This method quantifies the intensity of each factor to represent cause-and-effect category and used to establish dyadic relationship among the factors (Virmani et al., 2022). In scholarly literature, this technique is used in variety of applications including lean six sigma 4.0 (Samanta et al., 2023); net zero adoption (Virmani et al., 2022) and Coal Power Transition (Li et al., 2023).

The experts' ratings were taken using fuzzy scale as mentioned in Table 1. Let l, m and r represent lower, middle, and upper limit values of triangular fuzzy number. Suppose $Z^{p}_{ij} = (l^{p}_{ij}, m^{p}_{ij}, r^{p}_{ij})\ where 1 \le p \le P$, represent the fuzzy rating of pth expert by which attribute i affects attribute j.

Step 1: Pairwise comparison matrix is developed among selected enablers, the diagonal elements are represented using Not Important (NI).

Step 2: Normalization of fuzzy numbers

$$yl^{p}_{ij} = \frac{\left(l^{p}_{ij} - \min\limits_{1\le p\le P} l^{p}_{ij}\right)}{\Delta^{\max}_{\min}} \qquad (6)$$

$$ym^{p}_{ij} = \frac{\left(m^{p}_{ij} - \min\limits_{1\le p\le P} l^{p}_{ij}\right)}{\Delta^{\max}_{\min}} \qquad (7)$$

$$yr^{p}_{ij} = \frac{\left(r^{p}_{ij} - \min\limits_{1\le p\le P} l^{p}_{ij}\right)}{\Delta^{\max}_{\min}} \qquad (8)$$

Where $\Delta^{\max}_{\min} = \max r^{p}_{ij} - \min l^{p}_{ij}$

Step 3: Estimation of left and right normalized values

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$$yls^{p}_{ij} = \frac{ym^{p}_{ij}}{\left(1 + ym^{p}_{ij} - yl^{p}_{ij}\right)} \tag{9}$$

$$yrs^{p}_{ij} = \frac{yr^{p}_{ij}}{\left(1 + yr^{p}_{ij} - ym^{p}_{ij}\right)} \tag{10}$$

Step 4: Computation of total normalized crisp value

$$y^{p}_{ij} = \frac{yls^{p}_{ij}\left(1 - yls^{p}_{ij}\right) + yrs^{p}_{ij}}{\left(1 + yrs^{p}_{ij} - yls^{p}_{ij}\right)} \tag{11}$$

a. Computation of crisp value (CV) of p^{th} expert

$$CV^{p}_{ij} = \min_{1 \le p \le P} l^{p}_{ij} + y^{p}_{ij} \Delta^{\max}_{\min} \tag{12}$$

b. Calculation of integrated score to develop initial direct-relationship matrix

$$b_{ij} = \frac{1}{P} \sum_{p}^{1 \le p \le P} CV^{p}_{ij} \tag{13}$$

Where $B = [b_{ij}]$, where B is non-negative matrix of order nxn and b_{ij} represents the direct effect of attribute i on attribute j

Step 5: Evaluating normalized direct relation matrix

$$S = \frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} b_{ij}} B \tag{14}$$

Step 6: Computation of Total Relation Matrix

$$C = S(1 - S)^{-1} \tag{15}$$

Where, S is the normalized direct relation matrix

Step 7: Evaluating the prominence and influencing power of each enabler

In this step, row and column sum is evaluated using equation (16) and equation (17). D+R represents the prominence and D-R represents the influence.

$$D = \sum_{1 \le j \le n} c_{ij} \tag{16}$$

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$$R = \sum_{1 \le i \le n} c_{ij} \qquad (17)$$

Where c_{ij} indicates indirect effect by which attribute i impacts attribute j. D and R indicates the sum of rows and columns respectively.

3.3 Graph Theory Matrix Approach (GTMA)

The GTMA approach is a method of solving complex problems by representing the problem using digraphs. This approach can examine problems that involve relationships or connections between different elements or variables. The graph theory is applied in a variety of applications by researchers, including Industry 4.0 implementation (Virmani et al., 2021), technology adoption in logistics (Kumar et al., 2023b), Resilience of traffic networks (Dunn and Wilkinson, 2016), and Quality Management (Ali et al., 2022). GTMA can also be applied to analyze the corporate readiness towards AI adoption in HSCM. Moreover, the case organization can be assessed against maximum and minimum values, so that organizations get clear-cut idea about present situation and design suitable strategies to overcome the roadblocks to adopt concept or technology (Virmani et al., 2021). For this purpose, permanent function value is calculated, which is a standard function for evaluating matrix as defined in combinatorial math. It is evaluated using standard steps as in evaluating determinants, the only difference is all negative signs are replaced by positive ones (Grover et al., 2006).

Steps involved in graph theoretic approach are as follows:

Step1: Categorize the enablers into different categories.

Step2: Construct the digraph at system level for all categories of enablers.

Step3: Develop the digraph at sub-system level for every category of enablers.

Step4: Put the value of inheritance on the scale of 1-9 and interdependencies on 1-5 scale.

Step5: Computation of permanent function value (PFV) of matrix at sub-system level

Step6: Examine PFV of matrix at system level.

Step7: Compare PFV (computed in step 6) with maximum and minimum value.

Permanent function value can be computed as:

$$Per(E) = \prod_{1}^{4} E_i + \sum_i \sum_j \sum_k \sum_l e_{ij} e_{ji} E_k E_l + \sum_i \sum_j \sum_k \sum_l (e_{ij} e_{ji} e_{ki} + e_{ik} e_{kj} e_{ji}) E_l + \sum_i \sum_j \sum_k \sum_l (e_{ij} e_{ji})(e_{kl} e_{lk}) + \sum_i \sum_j \sum_k \sum_l (e_{ij} e_{jk} e_{kl} e_{li})(e_{il} e_{lk} e_{kj} e_{ji}) \quad (18)$$

Where E_i^s represent enablers category and e_{ij} represents interaction of i[th] enabler with j[th] enabler.

4. Case Illustration

In India, healthcare sector has emerged as one of the largest sectorial domains (IBEF, 2023). The low-cost healthcare solution in the country is attracting medical tourism from all over the globe. The healthcare sector has introduced 2.7 million additional jobs in the last five years (IBEF, 2023). Being one of the top developing economy, India is keenly facilitating the use of emerging technologies to make the health care supply chain more efficient, responsive, and flexible. The application of AI is unveiling strategic tools for diagnosing and treating patients. Countries across the globe are taking initiatives to adopt AI in healthcare, global market is expected to rise $188 billion by 2030 (Stewart, 2023).

Based on a literature review and discussion with experts, an initial list of enablers of AI adoption in HSCM was developed. Firstly, twenty-three enablers were identified, followed by a collection of survey responses from 10 experts working in the healthcare sector. The expert's profile is shown in Table 2. As per Bouzon et al. (2016) and Ma et al. (2011) the size of the expert panel members considered is acceptable. The criteria for selecting the expert were sound knowledge of healthcare supply chain and emerging technologies. The results of fuzzy-Delphi, Fuzzy-DEMATEL, and GTMA are discussed in following sections.

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Table 2: Experts' Profiles

Experts code	Designation	Experience (Yrs)	Key responsibilities
P1	Deputy Manager-Logistics	18	To oversee and facilitate effective supply chain and logistics management comprising procurement, distribution, transportation, and storage.
P2	Senior Manager-Logistics	14.5	Accountable for effective management of supply chain activities, including timely distributions, optimized inventory levels, and minimizing supply-demand mismatch.
P3	Manager-IT	13.8	Develop, strengthen, and maintain IT facilities and infrastructure as per company requirements.
P4	Manager-Technology assurance	16.8	Adopt contemporary and digital technologies to smoothen healthcare operations and enhance HSCM performance.
P5	Manager-Supply Chain Analyst	17.4	To analyze data and information about different supply chain functions and investigate areas for improvement.
P6	Senior Manager-Business development	15.8	To help the organization enhance financial growth by exploring and pursuing new business openings and collaborations.
P7	Deputy Manager-Software Development	18.7	Developing and maintaining software for effectively handling patients' data and examining medical records.
P8	Consultant-ERP	15.4	To provide technical support, train stakeholders, and optimize ERP systems.
P9	Manager-cyber security	14.2	To take measures against data breaches by robust cybersecurity measures and ensure data and information security.
P10	Senior Analyst-supply chain management	17.9	To carry out statistical analysis and assess demand patterns, perform forecasting analysis, and develop reports for effective decision-making

4.1 Results based on Fuzzy-Delphi: Standard reference procedure of fuzzy-Delphi Method (Karam et al., 2021), was used. The operating steps of fuzzy-Delphi technique are discussed in section 3.1. The fuzzy-Delphi results are shown in Table 3, the average of all enablers is computed to be 0.579. Eventually, the enablers having defuzzification values greater than the threshold value (0.579) were selected, otherwise rejected as suggested by Karam et al., (2021). In the presented research problem, out of twenty-three enablers*,* three enablers were screened i.e., Asset Management (E10), Matching business cases with healthcare supply chain capability (E11), Visibility and dynamic capabilities of HSCM (E19). The remaining twenty enablers

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were selected for carrying out further analysis. Therefore, the list of enablers of AI in HSCM is shown in Table 4.

Table 3: Fuzzy-Delphi Results

Enabler of AI in HSCM	**Fuzzy Weight Value**			**De-fuzzified Weight**	**Decision**
	Min	**Geometric Mean**	**Max**		
E1	0	0.767	1	0.589	Selected
E2	0	0.745	1	0.582	Selected
E3	0.25	0.542	1	0.597	Selected
E4	0.25	0.521	1	0.590	Selected
E5	0	0.822	1	0.607	Selected
E6	0.25	0.565	1	0.605	Selected
E7	0.25	0.536	1	0.595	Selected
E8	0	0.776	1	0.592	Selected
E9	0.25	0.736	1	0.662	Selected
E10	0	0.423	1	0.474	Rejected
E11	0	0.000	1	0.333	Rejected
E12	0.25	0.521	1	0.590	Selected
E13	0.25	0.542	1	0.597	Selected
E14	0.25	0.521	1	0.590	Selected
E15	0	0.754	1	0.585	Selected
E16	0	0.754	1	0.585	Selected
E17	0.25	0.598	1	0.616	Selected
E18	0.25	0.536	1	0.595	Selected
E19	0	0.542	1	0.514	Rejected
E20	0.25	0.605	1	0.618	Selected
E21	0.25	0.612	1	0.621	Selected
E22	0	0.754	1	0.585	Selected
E23	0.25	0.581	1	0.610	Selected

Threshold Value= 0.579

Table 4: Enablers of adopting AI in Healthcare Supply Chain

Enablers	**Enablers of AI in HSCM**	**Category**	**References**
E1	Budgetary allocation for adopting AI in health care (O1)	Organizational (O)	Gezgin et al. (2017); Ivanov et al. (2019); Kumar et al. (2023a)
E2	Support from top management for AI applications for responsiveness (O2)		Merhi & Harfouche (2023); Kumar et al. (2023a)
E3	Organization culture for adopting AI in HSCM (O3)		Behl et al. (2022); Kumar et al. (2023a)
E4	Aligning strategies for AI adoption in HSCM (O4)		Kumar et al. (2023a); Sharma et al. (2022)
E5	Supply Chain Integration across various linkages of healthcare supply chain (O5)		Bechtsis et al. (2018); Garay-Rondero et al. (2020)
E6	Decentralization to enable quicker decision making across various linkages of HSCM (O6)		Kazemi et al. (2019); Mathivathanan et al.(2021)

Enablers	Enablers of AI in HSCM	Category	References
E7	Change management for adopting AI in healthcare (O7)		Alicke et al. (2021); Dolgui and Ivanov (2022)
E8	Motivation of employees to adopt new technology in HSCM (B1))	Behavioral (B)	Damoah et al. (2021)
E9	Focus on Human Centred Design for effective implementation of AI in HSCM (B2)		Kumar et al. (2023a); Ivanov (2022)
E12	Skilled workforce for AI applications in HSCM (B3)		Ransbotham et al. (2017); Kumar et al. (2021); Kumar et al. (2023a); Virmani & Salve (2021);
E13	Coordination among cross-functional teams working for AI in HSCM (B4)		Fountaine et al. (2019); Virmani et al. (2021); Abadie et al. (2023)
E14	Scalability and Traceability of information flow across HSCM (T1)	Technological (T)	Dwivedi et al. (2021); Maheshwari et al. (2021);
E15	Reliable data for training and testing across various applications of AI in HSCM (T2)		Benzidia et al. (2021); Maheshwari et al. (2021)
E16	Strong IT infrastructure for information flow across HSCM (T3)		Frank et al. (2019); Lee and Yoon (2021)
E17	Technological maturity and sophistication for AI adoption in HSCM (T4)		Oliveira-Dias et al. (2022)
E18	Interoperability policies for adopting AI in HSCM (T5)		Vernadat et al. (2018); Maheshwari et al. (2021)
E20	Government policies and support for adopting AI in healthcare (EN1)	Environmental (EN)	Kazemi et al. (2019); Kumar et al. (2023a)
E21	Cyber security policies and regulations for AI applications (EN2)		Benzidia et al. (2021); Dolgui (2022), Kumar et al. (2022b)
E22	Competitive and mimetic pressure to adopt AI in HSCM (EN3)		Kumar et al. (2022a)
E23	Policy frameworks for spreading awareness for AI in HSCM (EN4)		Modgil et al. (2022); Ivanov (2022)

4.2 Results based on Fuzzy-DEMATEL

The cause-effect relationship among enablers of AI in HSCM were investigated using fuzzy – DEMATEL approach. D and R values are calculated using equation (16) and equation (17). The enablers were categorized in to cause and effect categories based on (D-R) values, where D and R represents row and column sum respectively. Furthermore, the sensitivity analysis results are also shown in this section. The results of the fuzzy-DEMATEL analysis are shown in Table 5. The results shown in Figure 2 help to understand the causal relationship among the

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identified enablers. The cause category includes thirteen enablers while the effect category includes seven enablers.

Usually, a complex relationship is observed between the enablers for decision-making (Feng & Ma, 2020). Therefore, it is imperative to understand the causal relationship among the identified enablers. The integration of fuzzy concepts along with the DEMATEL approach simplifies the decision-making process and draws more concrete solutions. The enablers whose (D-R) value is positive fall under the cause category, while the enablers with negative (D-R) value are placed under the effect group. The value of (D+R) represents the prominence of enablers. The cause category enablers are influencer ones, while the effect category enablers get influenced. The enablers are prioritized based on (D+R) value.

The rank order is computed as E13> E3> E5> E2> E12 > E4 > E16> E6> E7> E17> E8> E9> E15> E18> E1> E22> E14> E20> E21> E23. Coordination among cross-functional teams working for AI in HSCM (E13) has the highest (D+R) value of 11.210 and ranked first among the identified enablers. The D and R values for E13 were 5.488 and 5.722 respectively. AI adoption in HSCM is not a plug-and-play exercise; cross-functional teams from various domains profoundly impact its successful adoption (Fountaine et al., 2019). Moreover, cross-functional teams must collaborate and develop innovative solutions to enhance the performance of HSCM. Organizational culture for adopting AI in HSCM ranked second, having a (D+R) value of 11.114. The working ecosystem has a strong impact through its values, beliefs, vision, and mission. Similar findings were reported by Behl et al. (2022), who conducted an empirical analysis to understand the role of organizational culture in successful AI adoption.

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Table 5: Cause-Effect Relationship of enablers of AI in HSCM

Notation	Enabler of AI in HSCM	D	R	D+R	D-R	Category
E1	Budgetary allocation for adopting AI in health care	5.309	2.970	8.279	2.339	Cause
E2	Support from top management for AI applications for responsiveness	6.665	3.717	10.383	2.947	Cause
E3	Organization culture for adopting AI in HSCM	5.905	5.209	11.114	0.696	Cause
E4	Aligning strategies for AI adoption in HSCM	4.729	5.401	10.130	-0.671	Effect
E5	Supply Chain Integration across various linkages of healthcare supply chain	4.952	6.104	11.057	-1.151	Effect
E6	Decentralization to enable quicker decision making across various linkages of HSCM	4.499	5.451	9.950	-0.951	Effect
E7	Change management for adopting AI in healthcare	5.963	3.955	9.919	2.007	Cause
E8	Motivation of employees to adopt new technology in HSCM	4.896	4.223	9.119	0.672	Cause
E9	Focus on Human Centred Design for effective implementation of AI in HSCM	3.859	4.958	8.817	-1.098	Effect
E12	Skilled workforce for AI applications in HSCM	6.779	3.543	10.322	3.235	Cause
E13	Coordination among cross-functional teams working for AI in HSCM	5.488	5.722	11.210	-0.234	Effect
E14	Scalability and Traceability of information flow across HSCM	1.727	3.301	5.029	-1.573	Effect
E15	Reliable data for training and testing across various applications of AI in HSCM	4.334	4.258	8.592	0.076	Cause
E16	Strong IT infrastructure for information flow across HSCM	5.833	4.244	10.077	1.589	Cause
E17	Technological maturity and sophistication for AI adoption in HSCM	5.611	4.217	9.828	1.393	Cause
E18	Interoperability policies for adopting AI in HSCM	4.103	4.386	8.489	-0.283	Effect
E20	Government policies and support for adopting AI in Healthcare	4.478	0.547	5.025	3.930	Cause
E21	Cyber security policies and regulations for AI applications	3.943	0.249	4.192	3.693	Cause
E22	Competitive and mimetic pressure to adopt AI in HSCM	4.942	0.255	5.198	4.687	Cause
E23	Policy frameworks for spreading awareness for AI in HSCM	1.553	0.253	1.807	1.299	Cause

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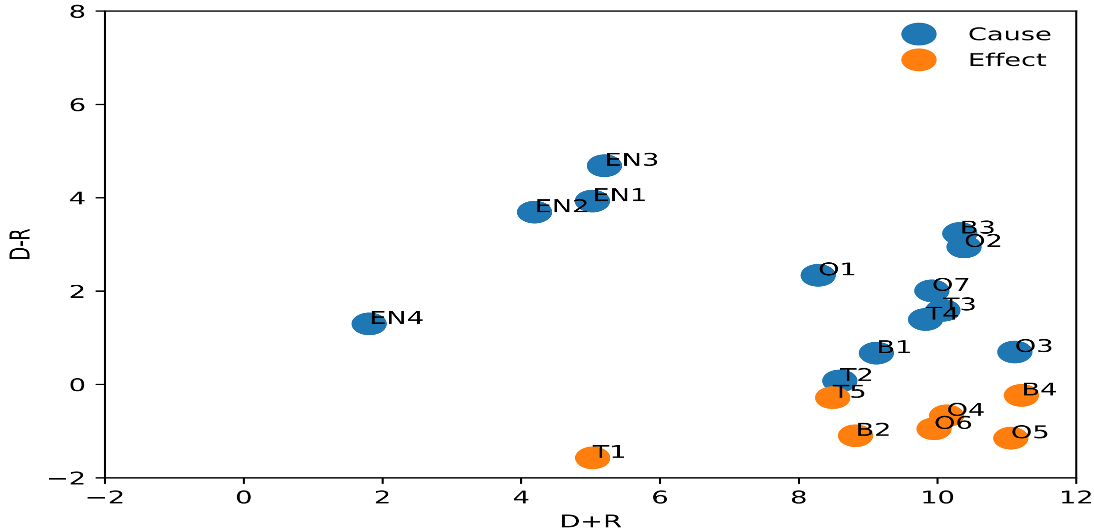

Figure 2: Cause-Effect Relationship among enablers of AI in HSCM

4.2.1 Sensitivity Analysis

To check the reliability of the enablers ranking, sensitivity analysis was carried out. We conducted five trials for the same; in the first trial, expert P1 was given a weightage of 0.4, while other experts were assigned a weight equal to 0.067. As a result, it is seen that Coordination among cross-functional teams working for AI in HSCM (E13), Organization culture for adopting AI in HSCM (E3), Supply Chain Integration across various linkages of healthcare supply chain (E5), Support from top management for AI applications for responsiveness (E2) found to be the top four enablers. Similarly, in the second trial, expert P2 was given a weightage of 0.4, while other experts were assigned a weight equal to 0.067. In this case, the top four enablers were E3, E13, E5, and E2. The process is repeated for five trials. The results are concluded in figure 3, Moreover, it is found that the ranking of enablers varied a little under different conditions.

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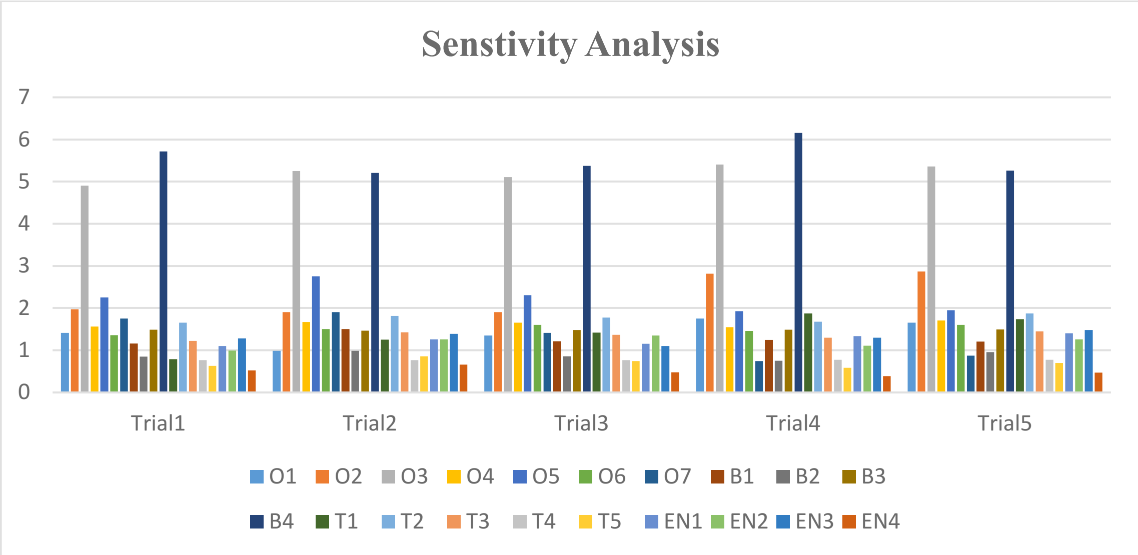

Figure 3: (D+R) Values of Different Enablers in Sensitivity Analysis

4.3 Results based on Graph Theory Matrix Approach (GTMA)

Based on the expert opinion, diagraphs were developed at system and sub system level. For instance, organizational and behavioral enablers affect each other, so bidirectional arrows are drawn between these two enablers. Similarly, diagraphs at sub-system level are prepared. Comprehensive Index (AI-HSCM) is evaluated by calculating permanent function value of case organization to assess readiness for AI adoption in HSCM on $\log_{10}$ scale.

The digraphs of enablers at system level are shown in Figure 4 and the digraphs of enablers at sub-system level are shown in Figure 5a to 5d. Bi-directional arrows are presented in black and uni-directional arrows are presented in red.

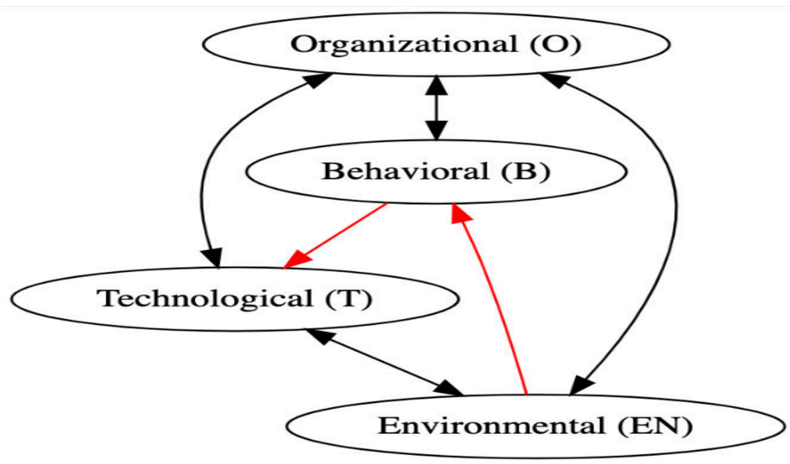

Figure 4: Digraph of enablers for adopting AI in HSCM

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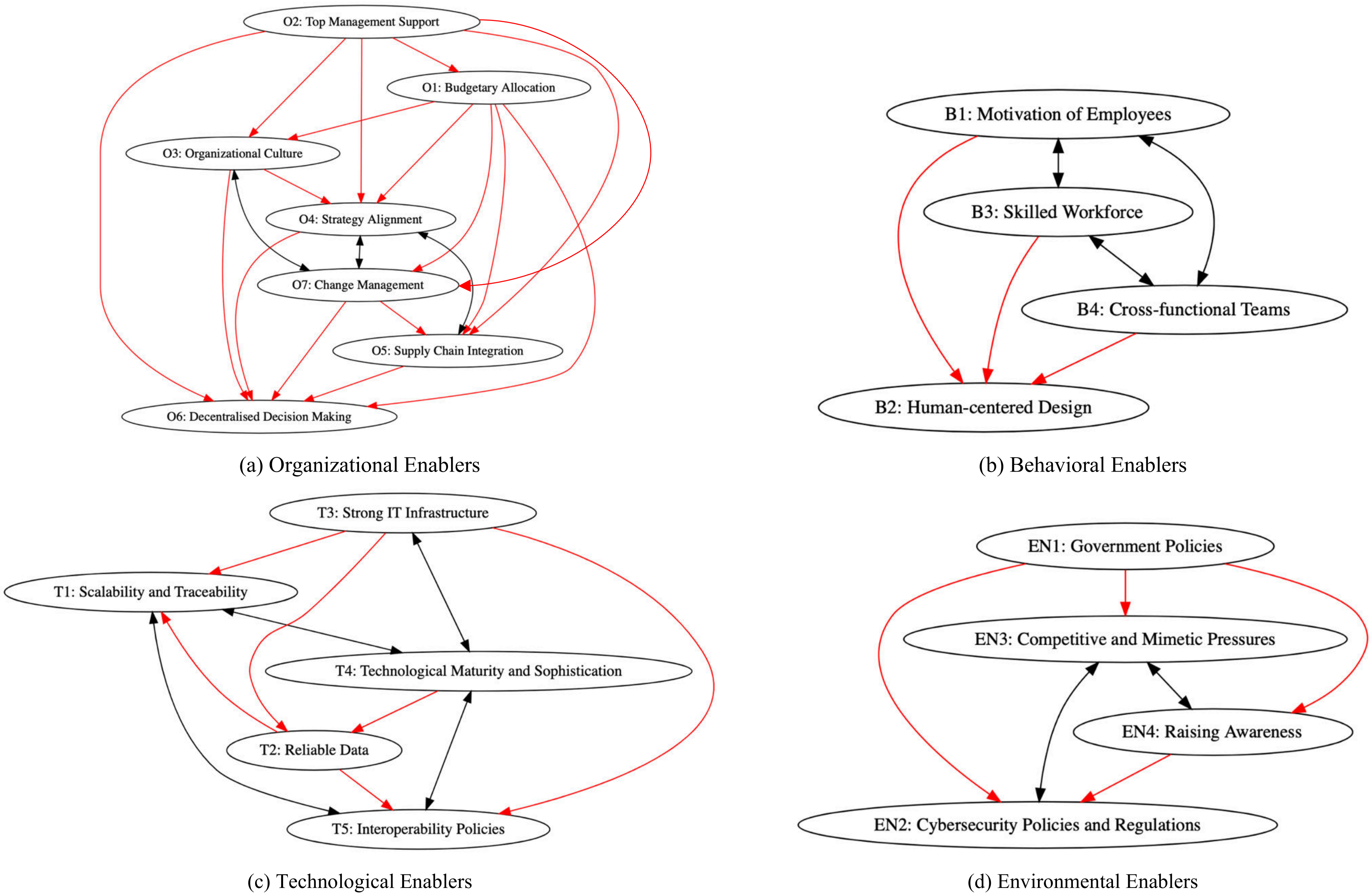

Figure 5: The digraphs of organizational, behavioral, technological, and environmental enablers

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The permanent function values of different categories of enablers are calculated and put in equation (18) to compute the permanent function value of (AI-HSCM) to assess readiness for AI adoption, as suggested by Aravind Raj et al. (2013).

The permanent function value of organizational category enabler is computed using equation (18) and is shown in equation (19). Its value comes out to be 1594656.

$$Per\ (O) = \begin{array}{c|c} Vertex & \begin{matrix} O1 & O2 & O3 & O4 & O5 & O6 & O7 \end{matrix} \\ \begin{matrix} O1 \\ O2 \\ O3 \\ O4 \\ O5 \\ O6 \\ O7 \end{matrix} & \begin{pmatrix} 7 & 0 & 3 & 2 & 3 & 4 & 2 \\ 5 & 8 & 5 & 5 & 4 & 4 & 2 \\ 0 & 0 & 6 & 4 & 0 & 4 & 3 \\ 0 & 0 & 0 & 7 & 4 & 4 & 3 \\ 0 & 0 & 0 & 4 & 6 & 4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 7 & 0 \\ 0 & 0 & 4 & 4 & 3 & 3 & 7 \end{pmatrix} \end{array} \quad (19)$$

On similar lines, permanent function of each category of enablers were evaluated. The permanent function values of behavioral, technological, and environmental enablers category were calculated to be 3828, 60006, and 3744 respectively. Substituting all these values in equation (18) to calculate permanent function values of (AI-HSCM) index as shown in equation (20)

$$\text{Permanent (AI-HSCM)} = \begin{array}{c|c} Vertex & \begin{matrix} O & B & T & EN \end{matrix} \\ \begin{matrix} O \\ B \\ T \\ EN \end{matrix} & \begin{bmatrix} 1594656 & 3 & 4 & 2 \\ 3 & 3828 & 4 & 0 \\ 4 & 0 & 60006 & 3 \\ 3 & 3 & 4 & 3744 \end{bmatrix} \end{array} \quad (20)$$

Comparison of permanent function value of AI-HSCM enablers of case organization against maximum and minimum value is shown in figure 6. The permanent function value of the case organization is computed as 1.37 x 10^{18}. Moreover, the maximum and minimum value are computed by putting diagonal elements 9 & 1 respectively. The corresponding maximum and minimum permanent function value of AI-HSCM enablers are computed as 1.06 x 10^{20} and 7.3 x 10^{9} respectively. Since the case-company value is very much closer to theoretically best-case

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value, therefore it can be concluded that case-company have strong prevailing enablers intensity towards AI-HSCM adoption.

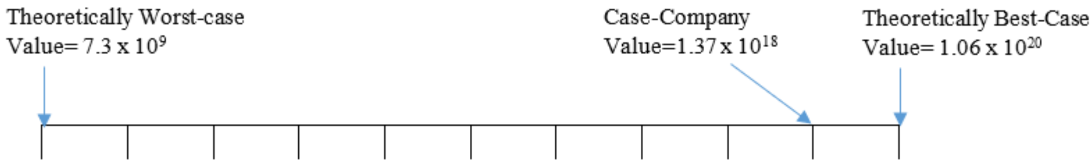

Figure 6: AI-HSCM Enablers Measurement Scale

5. Discussion

The proposed framework assessed the technological, organizational, environmental, and behavioral aspects of the enablers of AI adoption in HSCM. The enablers categorized under the Technology, Environment, Organization, Behavioral (TOE-B) framework (Tornatzky and Fleischer, 1990) help the practitioners understand these enablers comprehensively and prioritize them accordingly. This is because handling all the enablers is tedious, and it is unrealistic to expect the same level of attention on each of them. Therefore, hybrid decision-making approaches, including GTMA and fuzzy-DEMATEL, were used to further analyze enablers holistically. In the context of research findings and adding to existing literature, using the TOE framework, we systematically analyzed various enablers and determined their impact on supply chain performance. Understanding the criticality of enablers aids healthcare professionals in prioritizing them and taking strategic initiatives toward the successful adoption of AI. To the best of the authors' knowledge, this study is the first to assess the readiness of case organizations and develop a comprehensive AI-HSCM index. Since the concept of AI in HSCM is relatively novel, and it will take a few years for anticipated technologies to mature, there is an urgent need to carry out dedicated research and development activities that can guide healthcare organizations on their AI journey.

An effective healthcare supply chain is one of the key contributing factors in resource management, therefore ensuring timely and accurate delivery of medical products. It ultimately impacts patients' successful treatment and satisfaction levels. Adopting AI seems to have a plethora of benefits for both healthcare professionals as well as patients (Wani et al., 2024). Early detection of diseases enables doctors to start the right treatment on time so that the patient's life can be saved well before the situation turns worse. Moreover, the number of patients suffering from diseases can be drastically reduced. In recent years, during COVID-19, AI systems have been found to diagnose viruses and facilitate the development of vaccines (Yi et al., 2022). The presented study aimed at meeting following key research objectives. First, to establish an influential relationship among enablers for adopting AI in HSCM. Second, to develop a mathematical model to compute a comprehensive AI-HSCM index to analyze the industry's readiness for technology adoption using the GTMA approach.

Our research results show, under the "cause" category, environmental enabler 'Competitive and mimetic pressure to adopt AI in HSCM' (E22) is the most influencing enabler. Similar findings were reported by (Kumar et al., 2023a). The authors discussed that external factors, including competitive pressure, dynamic market conditions and regulatory frameworks, are strong influencers for adopting AI in HSCM. At times, organizations may be resistant to adopting emerging technologies, but competitive pressure forces them to come out of their comfort zones, break the shackles, and adopt emerging technologies.

Technological innovation in the healthcare sector has intensely changed the way the supply chain operates to make it more robust, responsive, and flexible. Intense competition creates a noticeable difference between the two organization types, investing in AI-based systems or not investing (Bughin & Seong, 2018). The research results will help medical professionals to meet patients' expectations by providing them with quality medical services and timely availability

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of medical goods, hence contributing enormously towards achieving the objective of successful treatment.

Another environmental category enabler E20, ‘Government policies and support for adopting AI in healthcare,’ ranked second under cause category. The government must act as a facilitator and promoter in adopting AI technological applications in HSCM. Similar findings were reported by Chatterjee (2020), who stated that governmental policies, rules, and regulations play a pivotal role in successful AI adoption in HSCM. Since the concept of AI in HSCM is relatively new, the government can act as a facilitator and provide technical guidance to healthcare professionals so that AI can be adopted successfully in HSCM. Moreover, the required advanced digital systems require substantial investment. Therefore, the government can provide sufficient funds or loans to small and medium-sized organizations to promote AI adoption in HSCM. ‘Cyber security policies and regulations for AI applications’ (E21) ranks third among the enablers in the “cause” category. Cyber-security is gaining momentum with an increased use of digital technologies. Cyber-security regulatory frameworks must be developed to protect the healthcare system and pertaining infrastructure. Similar results were found by Radanliev & De Roure (2023) who used AI to assess the cyber vulnerabilities of diseases.

Technological enabler, ‘Scalability and Traceability of information flow across HSCM’ (E14) ranked first under the “effect” category and has a (D-R) value of -1.573. Enhancing the scalability and traceability aspects helps to improve HSCM significantly. Adopting AI in HSCM helps healthcare professionals precisely predict the patient’s disease and start the right treatment accordingly at the earliest. Moreover, it helps to improve patient satisfaction by providing quality services and enhanced transparency, flexibility, and agility. The scalability feature ensures that a substantial amount of data can be accommodated in the HSCM system to increase the accuracy of the AI-based system. Moreover, precise applications of machine

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learning models facilitate knowing about patients' expectations and demand for medical products. Accordingly, strategic planning can be developed. It saves considerable time and money by route optimization for transporting goods and delivering services. Moreover, Ramzan et al. (2022) discussed similar findings, emphasizing that integrated AI-blockchain adoption in the pharmaceutical supply chain helps make it resilient, transparent, and traceable, helping to resolve counterfeit issues.

Moreover, organizational category enabler, 'Supply Chain integration across various linkages of the healthcare supply chain' (E5) is the second top enabler under the "effect" category. As HSCM is quite complex, there are issues of counterfeit products (Musamih et al., 2021). These issues can be handled using AI in conjunction with blockchain and big data analytics. Supply chain integration is a key factor for enhancing supply chain visibility which ultimately leads to better utilization of AI models. The results confirm those of Ivanov (2021). Moreover, in the present globalized scenario, the whole world is obsessed with data. Also, data is considered the new oil for industries. Additionally, Brown (2022) discussed the relevance of quality data to train AI systems and get precise results.

The graph theoretic matrix analysis (GTMA) results show the comprehensive index of AI in HSCM in an emerging economy context. The presented research results can be used to benchmark organizations seeking AI adoption to make the healthcare supply chain more agile and resilient. The research results reveal that the comprehensive index (AI-HSCM) value is $\log_{10}(1.37 \times 10^{18}) = 18.13$, while its maximum value is $\log_{10}(1.06 \times 10^{20}) = 20.02$ and minimum value is $\log_{10}(7.3 \times 10^{9}) = 9.86$. It shows that the case organization is well prepared for AI adoption in HSCM, leading to fruitful results. Furthermore, the value of organizational enabler is the highest among all the constructs, its value is $\log_{10}(1594656) = 6.20$, and the corresponding maximum and minimum values are 6.89 and 2.5, respectively.

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Healthcare organizations must have clearly defined policies, strategic alignment, and supply chain integration capabilities. Higher benefits of adopting advanced technologies are catching the interest of healthcare professionals to make huge investments. The return on investments is beyond the expectations of investors (Abadie et al., 2023). Moreover, Deveci (2023) mentioned that since the inception of new technologies, friction has existed against them. Also, as mentioned by the status quo bias theory (Shirish & Batuekueno, 2021), employees resist change and wish to refrain from adopting newer technologies. Therefore, effective change management strategies must address, encourage, and facilitate employees toward AI adoption in HSCM. Also, effective design thinking strategies can be adopted, which will help the practitioners and researchers to think out-of-box and explore feasible and viable solutions.

Furthermore, a collaborative culture facilitates the effective exchange of knowledge and information to adopt AI-based technologies. Abadie et al. (2023) also discussed that creative, innovative, and collaborative culture can provide consistent healthcare service quality. The second highest category is technological enabler. Because of complex systems and the introduction of newer technologies, there are no standard procedures available that may impede the adoption of AI in HSCM. Furthermore, organizations must have robust IT infrastructure and make dedicated efforts towards adopting updated technologies for successful AI adoption in HSCM. The findings are found to be like Kumar et al. (2021), who discussed that managers must identify the lacunas for adopting AI in healthcare supply chain and focus on various aspects such as employee training, building the required infrastructure, data quality and integrity. These results complement those reported by Deveci (2023) who discussed that technology, government support, and trialability are the most crucial factors for AI adoption in HSCM.

6. Theoretical and Managerial Implications

Industrialists, practitioners, and researchers agree that cutting-edge technologies are highly disruptive but unpredictive. Also, digital transformations have brought to the table various potential benefits for adopting AI in HSCM, which have a crucial role in enhancing the overall performance of organizations (Chatterjee, 2020).

6.1 Theoretical Implications

Although previous research studies explored the roadblocks and benefits of adopting AI in HSCM, there is lack of research pertaining to enablers for AI adoption in HSCM. The presented research study assessed the enablers of AI in HSCM using TOE-B framework. The study results highlight the key enablers contributing towards AI adoption in HSCM. Moreover, the dyadic relationship between enablers is developed and enablers are bifurcated into cause-and-effect categories using fuzzy-DEMATEL approach. It is seen that the majority of the enablers falls under cause category.

The fourth industrial revolution, also called Industry 4.0, has emerged as a boon for society. Various technologies encompassing under Industry 4.0 includes Artificial intelligence, machine learning, cyber-physical system, augmented reality, and virtual reality etc. Earlier, organizations were facing a dilemma that whether adopting AI in HSCM will bring out fruitful results or not. Nonetheless, now they have started understanding the strategic importance of AI in HSCM and initiated efforts to adopt it. The presented research results help in comprehensive assessment of key enablers and prioritize the key aspects for successful AI adoption in HSCM. However, AI adoption is subjected to various challenges including lack of reliability of data, lack of product uniformity. Since, in developing economies, the population is increasing, there is a need to strengthen and upgrade medical facilities. To handle this situation, AI is having untapped potential. However, proper analysis and results require precise medical data

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gathering. Senior healthcare professionals have agreed that adopting AI in HSCM is no longer a myth but will soon transform into reality. As the concept of AI in HSCM is relatively new, healthcare professionals must understand the enablers and work accordingly. Furthermore, as India is still in the infancy stage of adopting AI-based applications in the healthcare sector, effective governmental strategies can act as a strong facilitator. Moreover, incentives, recognition, and reward schemes can motivate budding technocrats and managers. The conduct of awareness programs, training, and educational programs focusing on using AI applications in the healthcare sector must be encouraged. Healthcare administration must strengthen IT facilities to tackle cyber-security issues so that global investors can be attracted to invest in the healthcare sector. As AI helps to predict demand patterns, inventories can be optimized resulting in reduced safety stocks, wastages and, hence achieving sustainability. Demand forecasting and planning can be done more precisely, thereby avoiding understock and overstock, and eliminating unnecessary transportation.

6.2 Managerial Implications

India is taking various initiatives towards digital healthcare systems. Under “Make in India”, and “National Digital Health Mission”, it is proposed to build digital infrastructure that is efficient, effective, affordable, timely, and safe. With the introduction of emerging technologies, senior-level officials, healthcare professionals, and practitioners must understand the importance of redesigning the healthcare supply chain to make it more resilient and responsive. Efficient and effective HSCM significantly impacts the lives of people. AI applications have the capacity to disrupt the healthcare supply chain. As AI adoption is at a nascent stage, its adoption is quite complex, there is a need to precisely understand the anticipated enablers. AI adoption can help healthcare professionals manage the inventory properly, handle risks, diagnose changes in disease trends, and make creative and effective decisions. Government must facilitate organizations to focus on research and development

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activities so that more viable solutions can be developed. Moreover, the government must provide funding schemes and develop knowledge centers to provide technical guidance for successful AI adoption in HSCM. The computed results reveal the relative importance of enablers for adopting AI in HSCM; managerial strategies can be developed accordingly. Furthermore, to keep pace with the market pressure, organizations need to adopt technological innovations and update themselves to serve the patients well and survive in a competitive environment. Moreover, organizations must focus on building absorptive capacity by investigating the antecedents since knowledge requirement is directly associated with day-to-day operational activities. AI in HSCM results in timely delivery of medicines, ensure quality of medical goods, therefore results in achieving sustainable development goals (SDGs), Good Health and Wellbeing (SDG3). Also, supply chain optimization results in cost and energy saving thereby helping in achieving carbon neutrality (SDG 13). Also, it results in achieving Industry Innovation and Infrastructure (SDG 9) and Sustainable Cities and Societies (SDG 11).

7. Conclusion, Limitations and Scope for Future Work

The adoption of AI in different industry domains including healthcare sector has skyrocketed in the past few years. Enhancing the performance of HSCM needs utmost attention as it directly affects the life of the people. The presented study analyzed the enablers of adopting AI in HSCM. In all, 23 enablers were identified using an extensive literature review. After collecting responses and analyzing enablers using the fuzzy-Delphi technique, three enablers were deleted, and twenty enablers are further investigated by using fuzzy-DEMATEL approach. Moreover, GTMA approach is applied to investigate the readiness of the healthcare industry to adopt AI in HSCM. Based on the findings of study, industry professionals can overcome the setbacks associated with adoption of AI in HSCM effectively. ‘Competitive and mimetic pressure to adopt AI in HSCM' is computed as most prominent causal enabler, whereas 'Scalability and Traceability of information flow across HSCM' is the most influenced one.

Like every research, this study also has some limitations. Since responses are collected from healthcare professionals in emerging economies like India, due to the easy accessibility of data collection in the home country, the research findings should be carefully thought before generalizing to other developing countries. Moreover, the results represent the reality in case Indian healthcare organization and can be considered for AI adoption in other healthcare organizations in India. Although we have taken utmost care in exploring the anticipated enablers using existing literature, a new set of enablers may emerge with time as the concept of AI in HSCM is evolving. Moreover, while going through the literature, we did not go through the doctoral theses' repositories due to unavailability of access, which can lead to some omissions. Therefore, future studies can include theses and technical reports. Also, our study included responses only from industry experts. However, the viewpoints of academic professionals can be different. Therefore, the academics could be invited to future studies to reflect both the academic and the industry perspectives. Since the presented research examined enablers using Multi-Criteria Decision-Making (MCDM) approaches, an empirical study can be conducted to validate the findings for the future research with broader scope. Furthermore, the challenges and solutions to adopting AI in HSCM can be explored and investigated by using fuzzy SWARA, fuzzy WASPAS, or other related techniques to establish how these methods compare against the method we used in this research.

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