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Original Article

Barriers to Artificial Intelligence-Driven Supply Chain Integration: An Interpretive Structural Modeling-Cross-Impact Matrix Multiplication Applied to Classification (ISM-MICMAC)-Based Analytics Modeling Approach

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Abstract

This study examines the barriers to incorporating Artificial Intelligence (AI) in supply chain management within Pakistan. Its primary objectives are to identify, hierarchically structure, and analyze the interrelationships among the obstacles impeding AI adoption, ultimately providing actionable recommendations for overcoming these challenges. Data were collected through an extensive literature review and expert interviews involving 26 specialists from academia and industry. The study employs Interpretive Structural Modeling (ISM) to map the complex interdependencies between the identified barriers and utilizes fuzzy Cross-impact matrix multiplication applied to classification (MICMAC) analysis to classify these barriers based on their driving and dependence powers. Key findings reveal that foundational issues such as Infrastructure Limitations, Data Challenges, and Security Concerns form the operational base that constrains AI integration. In contrast, independent barriers - specifically Government Support and Policy, along with Collaboration and Ecosystem Development - exert a significant influence over the entire system. The analysis indicates that while many barriers, including a shortage of a skilled workforce and ambiguous regulatory frameworks, are outcomes of systemic issues, addressing the independent barriers can trigger a cascading improvement across the system. The novelty of this study lies in its integrated methodological approach, combining ISM and fuzzy MICMAC, which allows for a detailed understanding of the hierarchical and causal relationships among barriers - a perspective that is less studied in the existing literature. The implications of this study are twofold: for policymakers, the study highlights the need for robust regulatory frameworks and enhanced public-private collaborations; for industry practitioners, it provides a strategic framework to prioritize investments in digital infrastructure, workforce development, and cybersecurity measures.

Categories: Strategic Supply Chain Management, Computational Intelligence and Information Management, Strategic Operation management

Keywords: artificial intelligence, supply chain management, barriers, ism, fuzzy micmac

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Introduction

Digital technologies, Artificial Intelligence (AI) in particular, are fundamentally transforming supply chain operations by introducing innovative tools and techniques that render these complex networks more efficient, resilient, and sustainable than ever before, as organizations increasingly harness machine learning, predictive analytics, and automation to optimize every facet of the supply chain (Belhadi et al., 2024). AI-driven technologies not only enable real-time data analysis for precise demand forecasting and dynamic inventory management but also facilitate proactive decision-making, streamline logistics, and enhance supplier collaboration, thereby transforming traditional linear supply chain models into agile, interconnected ecosystems that can rapidly adapt to disruptions, mitigate risks, and support sustainable practices through optimized resource allocation and waste reduction (Nweje and Taiwo, 2025).

For instance, companies such as Amazon and Walmart have leveraged AI to predict consumer demand and manage vast networks of warehouses and transportation routes, resulting in substantial cost reductions and enhanced customer service standards, while innovative startups across the globe are applying AI algorithms to monitor environmental impacts and ensure sustainable sourcing practices that contribute to a greener supply chain (Nweje and Taiwo, 2025); such examples clearly illustrate the vast potential of AI to revolutionize supply chain operations by not only increasing efficiency and reducing operational costs but also by fortifying the resilience of supply networks in the face of unforeseen challenges and aligning operational practices with the broader goals of sustainability. Despite these transformative benefits, the adoption of AI in the operations of supply chain has been notably sluggish, particularly in developing economies where digital transformation initiatives are frequently hindered by a lack of satisfactory preparation (Chanias et al., 2019), insufficient infrastructure (Ateeq, 2024), and unaddressed organizational barriers; many firms, while cognizant of the potential of AI to enhance logistics, procurement, and production planning, are reluctant to implement these technologies due to challenges such as regulatory uncertainty, a shortage of skilled professionals, fragmented data systems, and limited government support, all of which combine to create a formidable barrier to widespread AI integration. This slow pace of adoption is, in part, attributable to a fundamental lack of preparatory measures and strategic foresight prior to AI implementation, where companies often fail to identify, assess, and address critical hurdles such as the need for robust digital infrastructure, the importance of fostering a culture of data-driven decision-making, and the requirement for continuous investment in employee training and development to build an AI-ready workforce; without a comprehensive understanding of these prerequisites, organizations risk encountering operational disruptions and suboptimal outcomes, thereby stalling the broader diffusion of AI across supply chain functions.

Moreover, while a substantial body of literature has examined various barriers to AI adoption in supply chains, there remains a significant research gap in identifying which of these barriers are most critical and understanding the interrelationships among them; existing studies tend to treat obstacles such as infrastructure limitations (Kumar et al., 2023), regulatory and legal constraints (Singh, 2022), data quality issues (Lichtenauer et al., 2024), and workforce shortages in isolation (Ozkan-Ozen and Kazancoglu, 2022), neglecting the systemic interplay that can amplify their negative impact on AI integration. The objective of the study, therefore, is to systematically recognize and analyze the most significant barriers that impede the adoption of AI in supply chains, and to explore how these barriers interrelate, thereby providing a structured framework that not only highlights the hierarchical nature of these challenges but also offers insights into how addressing key issues can trigger a cascading positive effect throughout the entire supply chain ecosystem.

To achieve this, the research employs a blend of qualitative and quantitative methodologies, including a comprehensive systematic literature review to aggregate and synthesize current knowledge on AI adoption barriers, as well as advanced analytical techniques such as Interpretive Structural Modeling (ISM) and fuzzy Matrix Impacts Cross-Multiplication Applied to Classification (MICMAC) analysis (Zayed and Yaseen, 2021); these methodologies are particularly well-suited to capture the complexity of the interdependent relationships among barriers, as ISM facilitates the hierarchical structuring of these obstacles based on their driving and dependence powers, while fuzzy MICMAC analysis allows for the incorporation of uncertainty and subjectivity inherent in expert judgments, thereby providing a more nuanced and realistic depiction of the barriers' influence on one another (Hussain et al., 2024). This integrated approach is justified by

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the need for a holistic perspective that transcends traditional linear analyses, as the dynamic nature of supply chain environments and the rapid evolution of AI technologies demand methodologies that can effectively accommodate complex, multi-dimensional interdependencies.

Although prior approaches (Babu et al., 2021) have contributed valuable insights into individual challenges, they have often been limited by their inability to account for the systemic interactions that underlie AI adoption processes; in contrast, the combined use of ISM and fuzzy MICMAC not only enhances the analytical rigor of the study but also offers practical implications for both policymakers and industry practitioners by illuminating the critical leverage points where targeted interventions can yield the greatest impact. The study's contributions are multifaceted: it advances the academic understanding of AI adoption barriers by providing an integrated, systemic framework that maps the interrelationships among key obstacles, and it offers actionable insights for organizations seeking to implement AI in their supply chains by identifying priority areas for intervention, such as strengthening government support and policy frameworks, fostering collaboration between industry and academia, and investing in the development of a skilled workforce capable of managing and leveraging advanced AI technologies. In doing so, the research not only enriches the theoretical discourse on digital transformation and supply chain management (SCM) but also serves as a practical guide for decision-makers aiming to navigate the complexities of AI integration in an increasingly competitive and uncertain global market. Ultimately, by elucidating the critical barriers and their interconnected nature, this study provides a roadmap for overcoming the challenges that have historically impeded AI adoption in supply chains, thereby paving the way for more resilient, efficient, and sustainable operational practices that can drive long-term value creation and competitive advantage in an era of swift technological change and heightened market volatility.

Literature review

Before we explain the barriers of AI adoption, it is important to explain as to what is meant by AI. The concept of AI was first coined by John McCarthy in 1955 to investigate the abilities of machines to utilize language and tackle tasks typically handled by humans (McCarthy et al., 2006) (Pournader et al., 2021). AI stands for artificial intelligence which is a subfield of multidisciplinary sciences that generate intelligent systems. Usually, AI refers to the construction of systems that mimic or outperform human intelligence (Russell and Norvig, 2016) (Shrivastav, 2022). Over the years, the use of AI in SCM has helped smooth and streamline network operations using advanced options for data analysis and decision-making. It helps stake clearance of complex behavior patterns using classification, optimization, and clustering, which allow for a deeper understanding of supply chain dynamics. AI also helps to sense the environment to trigger autonomous actions, overcoming performance and quality issues. In addition, AI encourages negotiating on a joint collaborative model which encourages more efficiency and collaboration within the supply chain network. Scenario generation and simulating scenarios assist supply chain design, simulation, and planning with the help of data-driven solutions and predictive insights (Toorajipour et al., 2021) (Tsolakis et al., 2023).

Companies that effectively utilize and implement AI have two key characteristics that contribute to their success. The core of their methodology involves adopting a strong data culture guided by the data-informed decision-making principle. The second and most significant is the leadership that must invest in artificial intelligence training and employee advancement of skills in the company. The inherent complexity in the SCM integrates AI as a solution which on demand specification covers the entire network of supply chain participants along with the cooperation and information/data exchange across the network for optimal usage of AI (Shrivastav, 2022). The application of AI technology in supply chain operations can increase efficiency, accuracy, and decision-making processes (Pournader et al., 2021). The introduction of AI into Pakistan's supply chain systems is being impeded by substantial obstacles to implementation. The review synthesizes existing research to identify and categorize these impediments.

AI challenges in the light of literature

Infrastructure Limitation

One such barrier that is discussed in the aspect of AI application in the supply chain is the lack of infrastructure development, which is among the critical restrictions in enhancing AI-powered SCM systems. The Infrastructure Constraints encompass financial limitations, lack of knowledge, and inadequate infrastructure, which work together to impede smooth incorporation and productivity in the systems supporting supply chains in this century. Addressing these issues requires a systematic and targeted approach (Kumar et al., 2023).

Inadequate infrastructure can hinder scaling AI efforts, which tangentially limits businesses' ability to be innovative and stay competitive (Horowitz et al., 2022). Broadly speaking, it is still a major concern, as the high costs that come along with AI technologies, such as powerful hardware, secure storage for data, and reliable internet, are out of reach for many businesses, especially small- and medium-sized enterprises (Dwivedi et al., 2021). Budgetary limits are placed on the government, and there is inadequate investment, compelling businesses to rely on antiquated systems behind the curve of the digital revolution. Second, the problem is also driven by limited knowledge of the benefits of digital and AI technologies. Due to insufficient understanding of the applications of AI, organizations in many developing economies tend to perceive AI as overly complex or expensive. Firstly, organizational resistance to change and a lack of understanding about these tools limit their adoption and effectiveness (Božić, 2023). Additionally, underdeveloped infrastructure aggravates these challenges. Many organizations have been found wanting in terms of the digital architecture needed to sustain AI-powered systems such as high-speed, stable internet, reliable power generation, and scalable data storage facilities. AI requires data to train its algorithms for predictive analytics, and existing systems within organizations are usually not designed to provide the necessary data for AI and can be inefficient and a bottleneck (Khalid, 2024).

Skilled Workforce Shortage

A shortage of skilled workers poses a substantial obstacle to the development and advancement of digital and AI-driven supply chain systems across all levels of employment, including high-skilled, medium-skilled, and low-skilled positions (Chabilall et al., 2024). Doing so is crucial to fostering innovation and resilience across the sector. Support from extremely trained professionals such as data scientists or AI specialists is key to designing and managing complicated systems. Particularly in developing economies, the skills shortage breach between industries and academic institutions can result in a talent shortage that inhibits innovation and a lag in the inevitable pathway toward digital transformation (Kumba et al., 2024). Anticipate a similar emphasis on medium-skilled personnel, with operations managers and technical supervisors supporting the AI-driven system and ensuring the tools are used in day-to-day business operations. However, with substandard training programs, they cannot adapt to the evolving demands of digitized environments, establishing inefficient change processes and resistance to change (Bobitan et al., 2024). The low-skilled employees, who generally work in labor-intensive and manual jobs, are prone to displacement as automation through AI technologies becomes state-of-the-art. The failure to implement proper reskilling initiatives results in this sector being unable to assume different roles within digital supply chains, thereby creating operational gaps and defensive measures (Sinulingga et al., 2024). In developing economies, this shortage affects technology adoption, operational efficiency, and competitiveness. Combined with this, the exodus of consultants and the so-called brain drain leaves the local market deprived of a pool of talent. Collaboration between governments, educational institutions, and private organizations is essential to bridge these gaps (Fan, 2024).

Data Challenges

In order for any organization to be truly "AI-ready," it needs to be able to access a sufficiently large, diverse, and high-quality dataset, and the capability to process the data securely and within acceptable limits of privacy. Without this being actioned, the organization's capabilities with an AI system are unlikely to reach fruition and might also create new risks and complexities (Horowitz et al., 2022). Inadequate quality, lack of accessibility, and ethical issues surrounding big data deliver an important role in the acceptance and implementation of AI-based supply chains. AI is data-driven and requires high-quality, domain-specific, structured data to create models and enhance supply chain processes. In developing economies, data collection and maintenance are often not carried out properly due to outdated systems, uneven record-keeping, and limited technological resources. Reliable open datasets enable organizations to progress and allow AI tools to be used to enhance decision-making and efficiency.

Another important barrier is access to data. Even when good data does come along, it exists often in a silo among departments or organizations, creating hurdles for sharing and enabling use (Bull and Pratt, 2021). This value proposition becomes especially acute as small businesses struggle to compete while facing bureaucratic hurdles, proprietary lock-in, and other costs such as licensing fees or investments in integration work (Brall et al., 2022). Access to data is indispensable for collaboration and innovation in supply chains and will be best served by streamlining processes and ensuring equity.

Legal and ethical challenges, including issues such as data privacy, security, and ownership, compound the complexity. Many areas have weak legal structures, raising the potential for exploitation, violations, and customer distrust. These are ethical dilemmas, such as unfairness in data and algorithms, which highlight the importance of transparent and accountable practices (Reischauer and Ringel, 2022). Such challenges reinforce each other in a feedback loop that critically impedes AI adoption in supply chains. Inadequate quality data impacts AI model creation, and technology adoption hesitance stems from accessibility constraints and legal worries.

Government Support and Policy

The government can provide supportive legislation and policies, which can drive the implementation and optimization of digital AI-driven SCM systems. However, progress is stimulated by a variety of obstacles, from poorly defined technology-specific regulatory policies to weak public-private collaboration (Fransen et al., 2024). Addressing these challenges is essential to creating room for innovation, improving efficiency, and remain competitive on a global scale.

The information gap that we are facing can be seen as a significant barrier to government officials and other relevant parties who are responsible for the implementation and implementation of AI technologies. A limited understanding of the possibilities and possible uses of AI may hinder decision-making and make it difficult to adopt these transformative solutions (Wolniak and Stecuła, 2024).

Advanced supply chain technologies are held back by the lack of technology-specific policies in those countries. Most nations have no framework designed from the ground up for digital and AI-driven supply chains, and this is particularly true of developing economies. Policies to date have largely been high-level aspirational guides; there is limited business confidence or guidance on investment especially of the AI variety (Tan et al., 2024). In addition, governing uncertainty and a lack of standardization undermine local and international investments in local supply chain smart technologies. Governments often do not consult industry leaders, startups, and academia, and the policies become misaligned (Deep and Verma, 2023). The lack of incentives, grants, tax breaks, and other support removes even more reason to work together.

Such problems constitute a vicious cycle that throttles the promise of AI-powered supply chains. Unclear policies leave businesses without direction, while weak collaboration limits access to resources and new expertise (Bratt et al., 2021) (Saunila et al., 2024). Governments should focus on establishing targeted frameworks for ethical AI use, data-sharing protocols, and financial incentives. This not only helps in promoting state-of-the-art technologies of new private players but also aligns market needs with policy through innovation hubs and joint research programs (Abid et al., 2024) (Geny et al., 2024).

Regulatory and Legal Framework

A sound regulatory environment is essential for the implementation and usage of AI-powered supply chain solutions. However, the absence of solid guidelines makes it challenging to ensure the ethical and fair use of AI systems (Wolniak and Stecuła, 2024). Some challenges include the absence of comprehensive AI regulations and a general lack of awareness among the public which can slow down these frameworks. Many countries have outdated regulations that do not account for key areas like data privacy, algorithmic accountability, and ethical usage of AI (Feretzakis et al., 2024) (Arigbabu et al., 2024). Such regulatory void discourages investments, increases risks such as biased decision-making or data breaches, and stifles innovation and growth by leaving businesses in limbo without clear guidelines.

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However, a lack of public awareness makes it worse. Good regulations need the engagement of policymakers, business leaders, academics, and the public. But the absence of a clear understanding of what AI can help with and what the potential risks are starves public discourse about the economic, ethical, and social, consequences of AI, which leads to policies that are tangential to real-world concerns (Benefo et al., 2022) (Obasa and Palk, 2023). Over time, this leads to disconnected governance, weak frameworks, and a lack of accountability for governments and tech companies. This interconnected issue creates a cycle of stagnation where ambiguous regulations stifle innovation, and a lack of public awareness leads to lower pressure on policymakers. Governments and industry leaders need to step up to the plate and intentionally build comprehensive and inclusive regulatory frameworks to break this cycle. It demands guidelines for ethical AI use, data privacy, and accountability mechanisms (Oladele et al., 2024).

Collaboration and Ecosystem Development

To integrate and scale the digital and AI-driven supply chain systems, collaboration and ecosystem development are core capabilities needed for success. But weak linkages between academia and the corporate sector, and the lack of adequate startup support are limiting the growth of the ecosystem (Silveira et al., 2022). Overcoming these barriers is pivotal for innovation, efficiency, and sustainable operations in your supply chain.

Poor academia-industry partnership stifles ecosystem development; educational institutions create knowledge and develop skilled workers needed to meet global demand, and industry offers resources and experience needed to execute innovative knowledge (Magumba, 2022) (Park and Choi, 2023). Yet, a gap exists due to academic research leaning toward theory and industries not being able to communicate their needs clearly enough. This disparity leads to lost opportunities to create AI-driven solutions that address real-world problems. Mutual initiatives, like research partnerships and internships, are limited, further damping knowledge transfer and the adoption of technology (Suleman et al., 2021) (Wang et al., 2024). The challenges of ecosystems are also influenced by the lack of adequate startup support. Startups often serve as pioneers in the market, developing novel solutions to problems or identifying unmet needs in the market. Innovation and niche needs are addressed by startups, but they are hindered by challenges like restricted funding, guidance, and social connections. Lack of access to incubators, accelerators, and venture capital restricts their capacity to expand and commercialize new ideas. Entrepreneurial activity is hindered by regulatory obstacles and bureaucratic inefficiencies, thereby restricting the ability of startups to contribute to AI-driven supply chains (Güner Gültekin et al., 2025).

Security Concerns

Security concern proposes a major impediment for adoption of digital-AI-powered SCM systems, as cyber threats and data privacy constitute pain points in this sector (Wright, 2023). Other kinds of cyberattacks such as malware, ransomware, and phishing harm operations, put sensitive data at risk, and can result in loss of revenue. Dependence on IoT devices and cloud platforms is increasing the attack surface of supply chains, but many organizations do not put in place appropriate cybersecurity controls, like encryption and intrusion detection, which undermine operational stability and stakeholder confidence (Hockstad et al., 2025). Data privacy issues add an additional layer of complication to the usage of AI-based systems. Storing and exchanging massive amounts of data without sufficient protective measures or oversight puts organizations at risk for security breaches, regulatory infractions, and damage to their reputations. These challenges are compounded by ethical concerns, such as bias in algorithms and misuse of proprietary data (Hasan et al., 2024) (Kumar and Suthar, 2024) (Murphy et al., 2021). High stakes of data sharing without knowing what happens with that data pose a risk in a non-transparent and unsafe data life cycle.

Cybersecurity issues must be considered along with data privacy issues, yielding a complex environment (Deyannis et al., 2022) (Layode et al., 2024). Privacy breaches usually lead to cyber violations and weak data protection leads to cyber breaches. To combat these, organizations need to allocate budgets toward advanced cybersecurity tools, incident response teams, and periodic audits (Yaacob et al., 2023). To gain the trust of stakeholders, one needs to have clear policies regarding data, compliance with the rules and regulations, and transparency. Technologies enabling privacy, such as encryption and data anonymization, can limit risks as well (Ajala et al., 2024) (Marshall et al., 2022).

Economic and Political Stability

Political stability and economic stability are also critical enablers of adopting and operating AI-driven supply chain systems (Belhadi et al., 2024) (Usmani et al., 2023). Yet economic factors such as inflation, currency fluctuations, energy crises, and inconsistent policies present major obstacles to resilience in supply chains. Inflation raises the price of raw materials, labor, and technology, making it harder to manage budgets and make money. Fluctuating currency diminishes the certainty of cross-border trading, which creates a disincentive to foreign investors and difficulty in procurements that to some extent leads to financial insecurity for implementing technological solutions including AI (Kopych and Shevchuk, 2023).

Much of our economic stability depends on energy sources, and reliable, cheap energy is needed to run servers, IoT devices, and more. Power outages and an increase in energy prices disrupt operations, especially in developing economies where the grids are outdated (Ferhi and Kamel, 2024). The problem is compounded by policy inconsistency, with many abrupt changes in leadership and regulations leading to uncertainty and confusion, making it difficult to plan and invest for the long term. If the rules that apply to the future economy are uncertain or subject to rapid change, this destroys business confidence, slicing supply chains and encouraging businesses not to adopt new technologies like AI (Reynolds, 2024).

Continuous communication between individuals creates a self-reinforcing cycle of instability that hinders the development of efficient supply chain systems. Government officials and business leaders need to take steps to control inflation and currency fluctuations, promote investment in energy systems, particularly those powered by renewable resources, and implement unified regulations for digital and AI technologies in order to address this issue (Ososuakpor, 2021).

Figure *1* shows the barriers in implementing AI across the operations of SCM.

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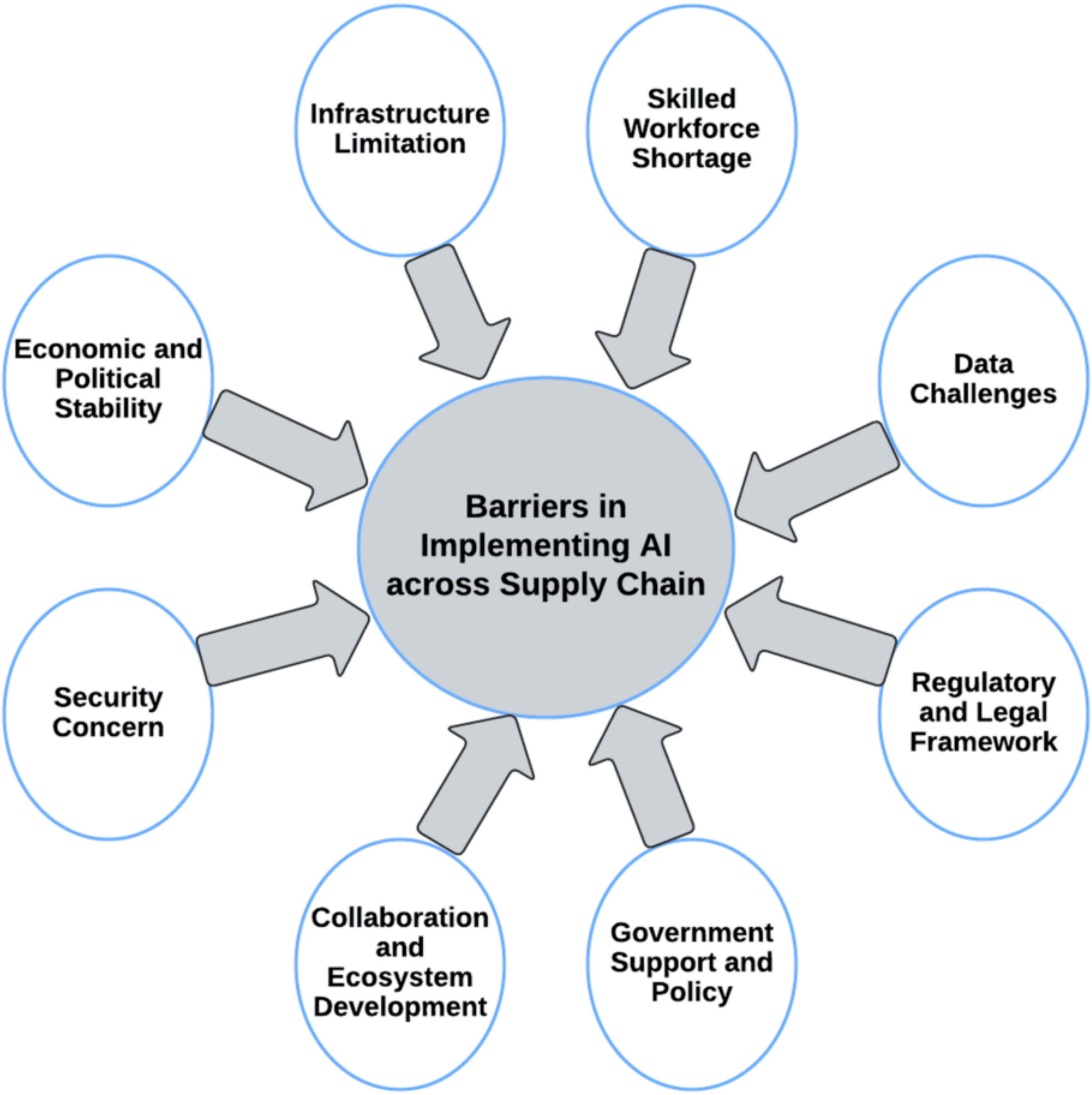

FIGURE 1: Barriers in Implementing AI

Source: Author. AI, artificial intelligence

Moreover, Table 1 shows the short description of the barriers in adopting AI in the operations of Supply Chain.

Main Variable	Description	Sub-variable	Reference
Infrastructure Limitation	Implementing AI often presents a challenge for many companies due to their existing legacy infrastructure. Current systems and software struggle to process extensive amounts of data within the necessary timeframe, thereby hindering and complicating the integration of AI technologies.	Financial constraints; Lack of awareness; Inadequate infrastructure	(Kumar et al., 2023)
Skilled Workforce Shortage	Skilled Workforce Shortage is the disparity exists between the demand for experts proficient in AI and the accessible talent pool, due to insufficient technical skills, like machine learning and data science, and AI model development, in addition to domain-specific knowledge necessary to integrate AI into different sectors.	High-skilled labor; Medium-skilled labor; Low-skilled workers	(Ozkan-Ozen and Kazancoglu, 2022) (Balsmeier and Woerter, 2019)
Data Challenges	Despite their ability to utilize vast amounts of information, AI systems can be hindered by the scarcity and variability of their available data. Even the most sophisticated AI systems can be compromised by inaccuracies or unavailability of data. The intelligence of any AI application is directly dependent on the data it can retrieve and utilize.	Limited availability of quality data; Data accessibility; Ethical and legal challenges	(Adhikary et al., 2021) (Lichtenauer et al., 2024) (Chikhaoui et al., 2022)
Regulatory and Legal Framework	As data-centric operations become more prominent, AI and other related activities are facing growing legal restrictions. Firms are required to adhere to these limitations, particularly when they function in sectors with strict	Insufficient public awareness and engagement; Lack of comprehensive AI regulations	(Singh, 2022) (Singh and Kumar, 2023)

	regulations, including finance and healthcare.		
Government Support and Policy	The complexities and hinderance in adoption of AI due to the regulation, initiatives and policy constraints by Government or State.	Lack of technology-specific policies; Weak public-private collaboration	(Kumar et al., 2023) (Lemay and Boggs, 2024) (Campion et al., 2020)
Collaboration and Ecosystem Development	The challenges faced by organizations in creating effective partnerships, integrating AI within existing ecosystems, and fostering industry-wide cooperation.	Limited academia-industry linkages; Insufficient support for startups	(Tavos, 2024)
Security Concern	With the advancement in technology, organizations encounter several hurdles and reservations when implementing AI owing to associated risks like privacy concerns, data security breaches, cybersecurity threats, and non-compliance with regulatory requirements.	Cybersecurity threats; Data privacy concerns	(Mukherjee and Mazumdar, 2019) (Rath and Kumar, 2021)
Economic and Political Stability	Uncertain economic conditions and unstable political environment hinder the successful implementation of AI across the operations of an organization.	Inflation and currency instability; Energy crisis; Policy inconsistency	(Dalyop, 2019) (Haynes, 2016) (Ejedegba, 2023)

TABLE 1: Barriers in Implementing AI

AI, artificial intelligence

Research Method

This research adopted an extensive literature-review to determine the substantial obstacles in integrating AI into supply chain operations. The ISM model effectively illustrates the complexity of a system by combining both visual graphics and text. The ISM model provided a useful framework for establishing connections between various components within a system (Wang et al., 2008) (Warfield, 1974). Zayed and Yaseen (Zayed and Yaseen, 2021) applied the ISM model to pinpoint obstacles hindering the implementation of sustainable SCM in Egyptian industries. Researchers identified key hurdles and interactions among these obstacles to develop a detailed model for understanding barriers and proposing strategies for addressing them. Babu et al. (Babu et al., 2021) employed the ISM model to examine prevalent risk factors

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and establish relationships among these risk factors within the context of Indian manufacturing Small and Medium Enterprises (SMEs). Godinho Filho et al. (Godinho Filho et al., 2022) examined the link between Industry 4.0 (I4.0) and the circular economy, which may enhance SCM performance, utilizing joint ISM and fuzzy MICMAC approach.

The ISM and fuzzy MICMAC method assists the examination of the transmission of impacts through reaction pathways and loops, thereby facilitating the creation of a hierarchy of barriers for incorporating AI into SCM processes. The ISM approach for identifying relationships among barriers relies on a consensus among expert opinions. The ISM methodology is adopted to analyze the interactions between the barriers. The barriers were categorized as per their driving power and dependence power, with the fuzzy MICMAC method being employed.

The four-step methodology, based on Godinho Filho et al. (Godinho Filho et al., 2022) and Govindan et al. (Govindan et al., 2015), involves the following steps: in the first step, an initial identification of barriers to integrating AI into the supply chain operations is conducted via a comprehensive analysis of existing literature, whereas the second step is to gather data through expert interviews to substantiate the initial findings from a practical standpoint; the third step involves the development of a structural model; and in final fourth step, the creation of a fuzzy MICMAC model accompanied by a cluster diagram highlighting driver and dependence power elements. The flowchart for the described method is illustrated in Figure *2*.

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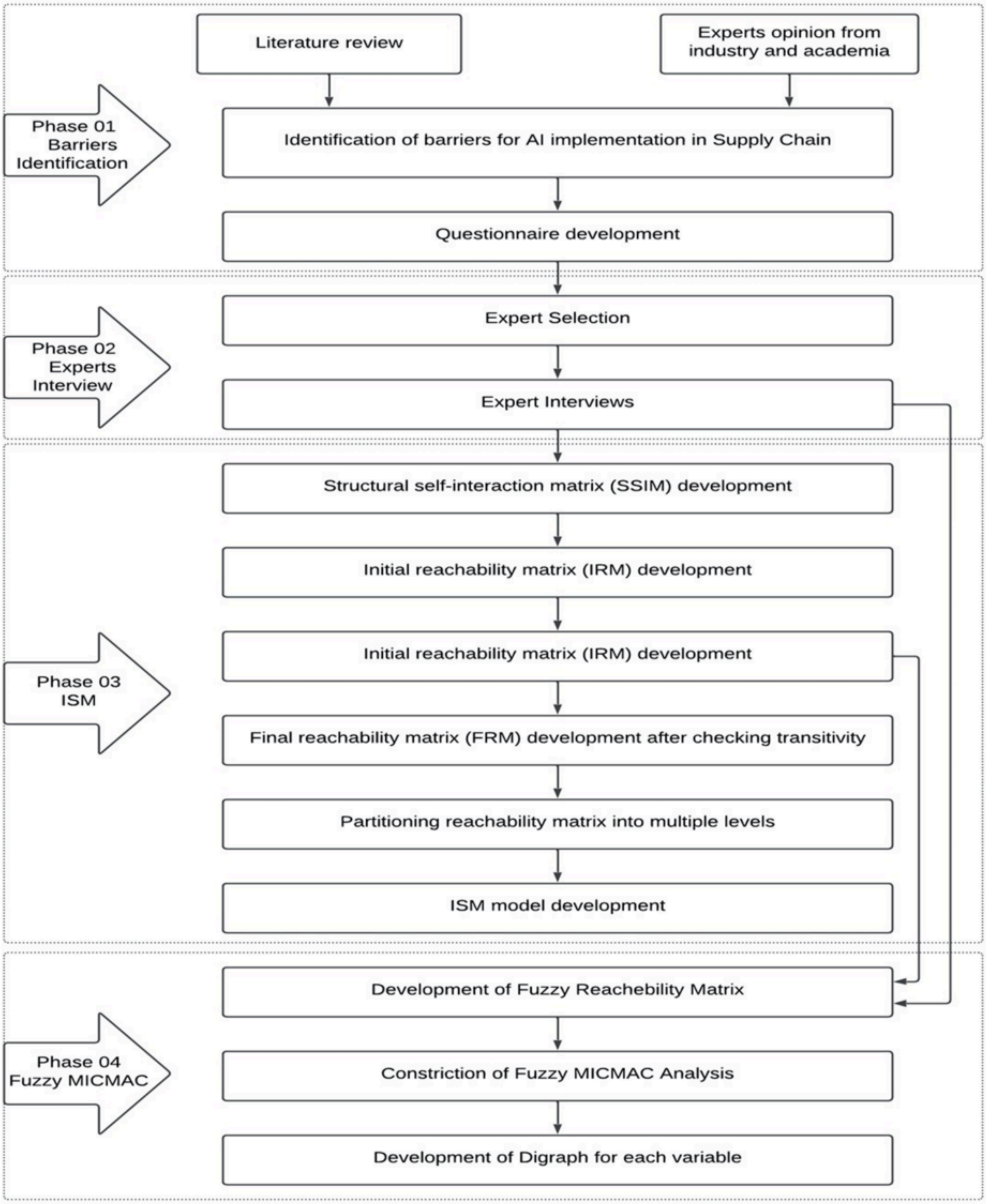

FIGURE 2: Flowchart Showing the Steps of Research Methodology

AI, artificial intelligence

Both primary and secondary research were undertaken to achieve the research goals of this investigation. The secondary research process entailed the identification of innovation factors through a thorough examination of existing literature. The main research techniques were employed to confirm the identified factors and examine their interconnections.

Selection criteria for respondents

The individuals selected for this research were chosen in consideration of their experience, technical abilities, and understanding of AI, industry, and SCM. The selection of practitioners was based on their holding senior management roles and their participation in various fields relevant to research subjects, thereby offering a comprehensive understanding and knowledge of Supply Chains and AI. For academic specialists, the primary requirements were demonstrating academic projects and publications relevant to the theme. The information gathered was crucial for this investigation to exclude individuals whose background was not pertinent to the research subject and area of focus.

The Structural Self-Interaction Matrix (SSIM) has been validated and proven robust because experts selected to contribute to its development meet at least one of the following conditions: (i) a minimum of 10 years of professional or academic experience, (ii) direct involvement in policy formulation, strategic decision-making, or implementation, or (iii) a record of peer-reviewed research or holding a senior managerial roles within the study's area of focus.

In this study, purposive sampling was employed and initially 42 experts were reached out via e-mail or telephone calls throughout the Pakistan. A total of 26 experts completed the questionnaire, which required them to fill out SSIM matrices. After collecting the questionnaires, data analysis was undertaken using the ISM methodology (Table *2*).

Category	Description	Number of Experts
Sector Affiliation	Academia (Universities & Research Institutes)	11
	Industry (Manufacturing, Logistics, Technology, Services)	9
	Policy/Government/Regulatory Bodies	6
Total		26
Years of Experience	10-15 years	8
	16-20 years	10
	>20 years	8
Highest Qualification	PhD	12
	Master's Degree	14
Primary Role	Senior Academic/Professor/Researcher	11
	Senior Manager/Director/Head of Department	9
	Policy Expert/Advisor/Regulator	6
Geographical Coverage	Multiple regions across Pakistan	26

TABLE 2: Profile of Experts Participating in the ISM Study

ISM, Interpretive Structural Modeling

ISM methodology

The procedural steps undertaken at this stage were suggested by Muruganantham et al. (Muruganantham et al., 2018). The correlation between the variables can be examined using SSIM based on the information gathered from the expert interviews. This matrix employs four symbols to denote the direction of relationships between the variables (Kannan et al., 2009):

• V: Element i directly influences or enables element j.

• A: Element j causes or facilitates element i.

• X: Elements i and j are dependent on each other.

• O: There is no relationship between elements i and j.

The final adjacent matrix was generated by combining the multiple SSIMs collected for each specialist, averaging them. A reachability matrix was constructed from the adjacency matrix and serves as the foundation for establishing the structural model. The binary matrix translates the adjacency matrix and its encoding symbols (V, A, X, O) into either 0 or 1. The reachability matrix was constructed in a two-stage process:

Stage One: Converting the adjacent matrix to a binary matrix in accordance with these guidelines (Godinho Filho et al., 2022) (Govindan et al., 2015):

When the SSIM matrix at (i,j) is V, the subsequent value in the reachability matrix at (i,j) is 1, while the value at (j,i) is set to 0.

When the SSIM at (i,j) is A, the entry at (i,j) in the matrix is set to 0, and the entry at (j,i) is set to 1.

When the (i,j) in the SSIM is X, the corresponding (i,j) and (j,i) values in the matrix are set to 1.

When the SSIM entry at position (i,j) is O, both the (i,j) and (j,i) entries in the matrix are then set to 0.

Elements on the diagonal are assigned a value of 1 when both their row (i) and column (j) indices are identical.

Stage Two: The ISM approach's transitivity is assessed by examining the relationships between variables in context, relying on the premise that if variable A is connected to variable B and variable B is connected to variable C, then variable A must be linked to variable C. The existence of transitivity indicates an indirect relationship between the variables, demonstrated by the entry of 1 in the matrix.

The reachability matrix can be computed following these two procedures, which enables the evaluation of influence and driving capability. The dependency power is determined by summing the total impact of all variables on a particular variable listed at the end, across the columns of the matrix. The driving power is determined by the total number of variables that a given variable influences, as illustrated by the figure in the last column and the corresponding row of the matrix. The reachability matrix obtained is subsequently decomposed into distinct levels, thereby determining the reachable set and the preceding set for each element in the matrix. The scope of a variable's influence encompasses not only the variable itself but also the other variables it directly impacts. The set is defined according to the equation presented in Equation (1). A specified variable's set of antecedents comprises the variable itself, and all other variables that influence it. The expression can be described in accordance with Equation (2), and the intersection set is constructed by means of the formula presented in Equation (3).

$$R(i) = \{j \in S \mid e_{ij} = 1\} \cup \{i \in S\} \quad (1)$$

$$A(i) = \{j \in S \mid e_{ji} = 1\} \cup \{i \in S\} \quad (2)$$

$$I(i) = R(i) \cap A(i) \quad (3)$$

In the ISM hierarchy, the variable whose accessibility and intersection sets are identical becomes the highest-level variable. The process continues by discarding the Level I variable and proceeding with the remaining variables in each step until all variable levels have been identified. The model has now been completed. The initial diagram is created by depicting each variable at its specific level, as outlined in the final reachability matrix. The relationships relating variables are demonstrated in the figure. To establish a connection among variables i and j, an arrow is drawn from i to j, transitive relationships are then eliminated, and the diagram is subsequently verified to prevent any inconsistencies from arising.

ISM fuzzy MICMAC analysis

Duperrin and Godet (Duperrin and Godet, 1973) developed the MICMAC as a structured approach to examining intricate problems. The outcomes of the ISM method are utilized as input for a fuzzy MICMAC analysis, which is employed to determine the driving and dependence power of barriers. This method, MICMAC, constitutes an indirect classification technique used to critically evaluate the scope of each element (Bhosale and Kant, 2016).

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The earlier input from the expert for the ISM analysis was binary in form, comprising only yes-no, true-false, or 1-0 responses. The relationship's existence is represented using either a positive or a negative value, with little consideration given to its actual intensity. The unclear strength of the relationships between any two inhibitors is a disadvantage of the ISM approach. The potential for robust or fragile, stable or unstable relationships has always been present in every situation. This limitation is not addressed within ISM. The ISM fuzzy MICMAC analysis is chosen to address this limitation. The following section provides a detailed, step-by-step explanation.

Calculation of Final Fuzzy Reachability Matrix through Aggregated SSIM

The procedural steps taken to develop fuzzy reachability matrix were suggested by Khatwani et al. (Khatwani et al., 2015). The linguistic terms and the values assigned to each linguistic terms are shown in Table *3*.

Linguistic terms	Linguistic values
Very High Influence (VH)	(0.75, 1.0, 1.0)
High Influence (H)	(0.5, 0.75, 1.0)
Low Influence (L)	(0.25, 0.5, 0.75)
Very Low Influence (VL)	(0, 0.25, 0.5)
No Influence (No)	(0, 0, 0.25)

TABLE 3: Linguistic Scales for Influence

The SSIM matrix is subsequently transformed into a fuzzy reachability matrix. The linguistic terms in the aggregated SSIM matrix are replaced with their equivalent fuzzy triangular linguistic values. The final fuzzy reachability matrix is constructed under specific requirements.

When the value at position (i,j) is V (VH): The entry at position (i,j) is represented by the values (0.75,1.0,1.0), while the entry at position (j,i) is (0,0,0.25).

When the value at position (i,j) is V (H): The value at position (i,j) is represented as (0.5,0.75,1.0), while the entry at position (j,i) is 0, denoted by (0,0,0.25).

When the value at position (i,j) is V (L): The value at position (i,j) is represented as (0.25,0.5,0.75), while the entry at position (j,i) will be 0, denoted by (0,0,0.25).

When the value at position (i,j) is V (VL): The entry at position (i, j) is represented as (0, 0.25, 0.5), while the entry at position (j, i) is zero, denoted by (0, 0, 0.25).

When the value at position (i,j) is A (VH): The entry at position (i, j) will be denoted by (0,0,0.25), signifying 0{No}, while the entry at position (j, i) can be represented by (0.75,1.0,1.0).

When the value at position (i,j) is A (H): The value at position (i,j) will be denoted as (0,0,0.25), signifying a value of zero. Conversely, the entry at position (j,i) can be represented as (0.5,0.75,1.0).

When the value at position (i,j) is A (L): The value at position (i,j) will be represented as (0,0,0.25) to indicate a value of zero. Similarly, the entry at position (j,i) can be represented as (0.25,0.5,0.75).

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When the value at position (i,j) is A (VL): The value at position (i,j) will be represented as (0,0,0.25), indicating a value of 0, while the entry at position (j,i) will be denoted as (0,0.25,0.5).

When the value at position (i,j) is X (VH): The value (i,j) will represented by (0.75,1.0,1.0) and entry (j,i) will also represented by (0.75,1.0,1.0)

When the value at position (i,j) is X (H): The value at (i,j) can be represented as (0.5,0.75,1.0) and the entry at (j,i) also be represented as (0.5,0.75,1.0).

When the value at position (i,j) is X (L): The value at position (i,j) can be represented by the values (0.25, 0.5, 0.75), and similarly, the entry at position (j,i) can be represented by the values (0.25, 0.5, 0.75).

When the value at position (i,j) is X (VL): Entry (i,j) can be represented by the (0,0.25,0.5) and similarly, entry (j,i) can be represented by the (0,0.25,0.5).

When the value at position (i,j) is X (VH,H): The entry at position (i,j) can be represented as (0.75,1,1), and the entry at position (j,i) can be represented as (0.5,0.75,1). Likewise, other potential scenarios include - X (VH, L), X (VH, VL), X (H, VH), X (H, L), X (H, VL), X (L, VH), X (L, H), X (L, VL), X (VL, VH), X (VL, H), X (VL, L).

When the value at position (i,j) is 0 (No): The entries at positions (i,j) and (j,i) are represented by the value (0,0,0.25).

The final fuzzy reachability is denoted as $\tilde{Z}$ in following Equation (4):

$$\tilde{Z} = \begin{bmatrix} \tilde{z}11 & \tilde{z}12 & \dots & \tilde{z}_{1n} \\ \tilde{z}21 & \tilde{z}22 & \dots & \tilde{z}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{z}n1 & \tilde{z}n2 & \dots & \tilde{z}_{nn} \end{bmatrix} \quad (4)$$

Where, $\tilde{z}_{ij} = (l_{ij}, m_{ij}, u_{ij})$

Determining Driving Power and Dependence for MICMAC Analysis Calculations

The fuzzy reachability matrix is produced by the aggregated fuzzy SSIM matrix in the preceding step. The driving power and dependence are determined by summing both rows and columns of the fuzzy reachability matrix, as per Equation (4).

Results

The results for the ISM analysis and fuzzy MICMAC analysis are shown in the following tables, from Table *4* to Table *9*.

The SSIM presented in Table *4* reflects the interconnecting relationships between components as perceived by the experts.

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Variables	Infrastructure Limitations	Skilled Workforce Shortage	Data Challenges	Regulatory and Legal Framework	Government Support and Policy	Collaboration and Ecosystem Development	Security Concerns	Economic and Political Instability
Infrastructure Limitations		A	O	O	A	A	O	A
Skilled Workforce Shortage			O	O	A	A	V	V
Data Challenges				O	A	A	O	A
Regulatory and Legal Framework					A	A	V	V
Government Support and Policy						A	V	V
Collaboration and Ecosystem Development							O	O
Security Concerns								A
Economic and Political Instability								

TABLE 4: Structural Self-Interaction Matrix (SSIM)

Where, V shows i directly influences j, A shows j directly influences i, X shows i and j are dependent on each other and O shows there is no relationship between elements i and j.

The Reachability Matrix (RM) presented in Table *5* is obtained from the SSIM to identify direct and indirect connections among variables.

Variables	1	2	3	4	5	6	7	8
Infrastructure Limitations	1	0	0	0	0	0	0	0
Skilled Workforce Shortage	1	1	0	0	0	0	0	1
Data Challenges	0	0	1	0	0	0	0	0
Regulatory and Legal Framework	0	0	0	1	0	0	1	1
Government Support and Policy	1	1	1	1	1	0	1	1
Collaboration and Ecosystem Development	1	1	1	1	1	1	0	0
Security Concerns	0	0	0	0	0	0	1	0
Economic and Political Instability	1	0	1	0	0	0	1	1

TABLE 5: Reachability Matrix (RM)

(1) Infrastructure Limitations, (2) Skilled Workforce Shortage, (3) Data Challenges, (4) Regulatory and Legal Framework, (5) Government Support and Policy, (6) Collaboration and Ecosystem Development, (7) Security Concerns, (8) Economic and Political Instability

The Final RM is presented in Table 6, following the application of the transitivity rule to the initial RM.

Variables	1	2	3	4	5	6	7	8	Driving Power
Infrastructure Limitations	1	0	0	0	0	0	0	0	1
Skilled Workforce Shortage	1	1	1*	0	0	0	1	1	5
Data Challenges	0	0	1	0	0	0	0	0	1
Regulatory and Legal Framework	1*	0	1*	1	0	0	1	1	5
Government Support and Policy	1	1	1	1	1	0	1	1	7
Collaboration and Ecosystem Development	1	1	1	1	1	1	1*	1*	8
Security Concerns	0	0	0	0	0	0	1	0	1
Economic and Political Instability	1	0	1	0	0	0	1	1	4
Dependence Power	6	3	6	3	2	1	6	5	

TABLE 6: Final Reachability Matrix

* The transitivity identified in the relationship between the variables.

The hierarchical structure of the elements is exposed in Table 7 through level partitioning, relying on their antecedent and reachability sets.

Elements (Mi)	Reachability Set R(Mi)	Antecedent Set A(Ni)	Intersection Set R(Mi)∩A(Ni)	Level
1	1,	1, 2, 4, 5, 6, 8,	1,	1
2	2,	2, 5, 6,	2,	3
3	3,	2, 3, 4, 5, 6, 8,	3,	1
4	4,	4, 5, 6,	4,	3
5	5,	5, 6,	5,	4
6	6,	6,	6,	5
7	7,	2, 4, 5, 6, 7, 8,	7,	1
8	8,	2, 4, 5, 6, 8,	8,	2

TABLE 7: Level Partitioning (LP)

Table 8 shows the Reduced Conical Matrix (CM), facilitating the construction of the structural model via the grouping of analogous components.

Variables	1	3	7	8	2	4	5	6	Driving Power	Level
Infrastructure Limitations	1	0	0	0	0	0	0	0	1	1
Data Challenges	0	1	0	0	0	0	0	0	1	1
Security Concerns	0	0	1	0	0	0	0	0	1	1
Economic and Political Instability	1	1	1	1	0	0	0	0	4	2
Skilled Workforce Shortage	0	0	0	1	1	0	0	0	5	3
Regulatory and Legal Framework	0	0	0	1	0	1	0	0	5	3
Government Support and Policy	0	0	0	0	1	1	1	0	7	4
Collaboration and Ecosystem Development	0	0	0	0	0	0	1	1	8	5

Dependence Power	6	6	6	5	3	3	2	1		
Level	1	1	1	2	3	3	4	5		

TABLE 8: Reduced Conical Matrix (CM)

The aggregated fuzzy RM in Table *9* improves the SSIM by including fuzzy values, which account for uncertainty in expert opinions.

Variables	1	2	3	4	5	6	7	8
Infrastructure Limitations	1	0	0	0	0	0	0	0
Skilled Workforce Shortage	H	1	0	0	0	0	0	L
Data Challenges	0	0	1	0	0	0	0	0
Regulatory and Legal Framework	0	0	0	1	0	0	H	H
Government Support and Policy	VH	H	L	VH	1	0	L	H
Collaboration and Ecosystem Development	H	L	L	H	H	1	0	0
Security Concerns	0	0	0	0	0	0	1	0
Economic and Political Instability	H	0	L	0	0	0	VH	1

TABLE 9: Aggregated Fuzzy Reachability Matrix Based on SSIM Matrix

The final fuzzy reachability matrix Z in Table *10* is accompanied by the fuzzy driving power and dependence power, both of which are essential for conducting a MICMAC analysis.

Variables	1	2	3	4	5	6	7	8	Dependence Power
Infrastructure Limitations	(1,1,1)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	1.41
Skilled Workforce Shortage	(0.5,0.75,1)	(1,1,1)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	3.30
Data Challenges	(0,0,0.25)	(0,0,0.25)	(1,1,1)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	1.41
Regulatory and Legal Framework	(0,0,0.25)	(0,0,0.25)	(0,0,0.25)	(1,1,1)	(0,0,0.25)	(0,0,0.25)	(0.5,0.75,1)	(0.5,0.75,1)	3.64
Government Support and Policy	(0.75,1.0,1.0)	(0.5,0.75,1)	(0.25,0.5,0.75)	(0.75,1.0,1.0)	(1,1,1)	(0,0,0.25)	(0,0,0.25)	(0.5,0.75,1)	7.55
Collaboration and Ecosystem Development	(0.5,0.75,1)	(0.25,0.5,0.75)	(0.25,0.5,0.75)	(0.5,0.75,1)	(0.5,0.75,1)	(1,1,1)	(0.25,0.5,0.75)	(0,0,0.25)	5.67
Security Concerns	(0,0,0.25)	(0.5,0.75,1)	(0,0,0.25)	(0.25,0.5,0.75)	(0.25,0.5,0.75)	(0,0,0.25)	(1,1,1)	(0,0,0.25)	1.41
Economic and Political Instability	(0.5,0.75,1)	(0,0,0.25)	(0.25,0.5,0.75)	(0.5,0.75,1)	(0.5,0.75,1)	(0.5,0.75,1)	(0.75,1.0,1.0)	(1,1,1)	4.43
Driving Power	5.86	3.44	3.79	3.9	2.35	1.49	4.56	4.43	

TABLE 10: Final Fuzzy Reachability Matrix Z With Fuzzy Driving Power and Dependence of Criteria

ISM analysis

The ISM methodology discloses significant information on the hierarchical connections between the obstacles to artificial intelligence integration in supply chains in Pakistan, as shown in Figure *3*. At the core of the hierarchy is Collaboration and Ecosystem Development, identified as Barrier 6, and it serves as the primary catalyst for addressing systemic obstacles. The absence of a unified system among stakeholders, encompassing industries, educational institutions, and governmental agencies, substantially hinders the implementation of artificial intelligence. Direct collaboration significantly impacts Government Support and Policy (Barrier 5), underscoring the necessity for well-rounded and supportive policies. The government's involvement has a direct influence on intermediate obstacles, including the Skilled Workforce Shortage (Barrier 2) and the Regulatory and Legal Framework (Barrier 4). The lack of adequately trained AI specialists and ambiguous legal regulations are obstacles that impede the seamless implementation of AI in supply chain functions. Downstream, economic and political instability (Barrier 8) becomes a substantial outcome of these disparities. At the operational level, Infrastructure Limitations, Data Challenges, and Security Concerns constitute the foundational barriers, specifically Barrier 1, Barrier 3, and Barrier 7. These challenges stem from systemic instability, posing significant technical and operational hindrances. The interconnected nature of these obstacles highlights the need to tackle problems at their source to prevent or minimize subsequent operational difficulties efficiently.

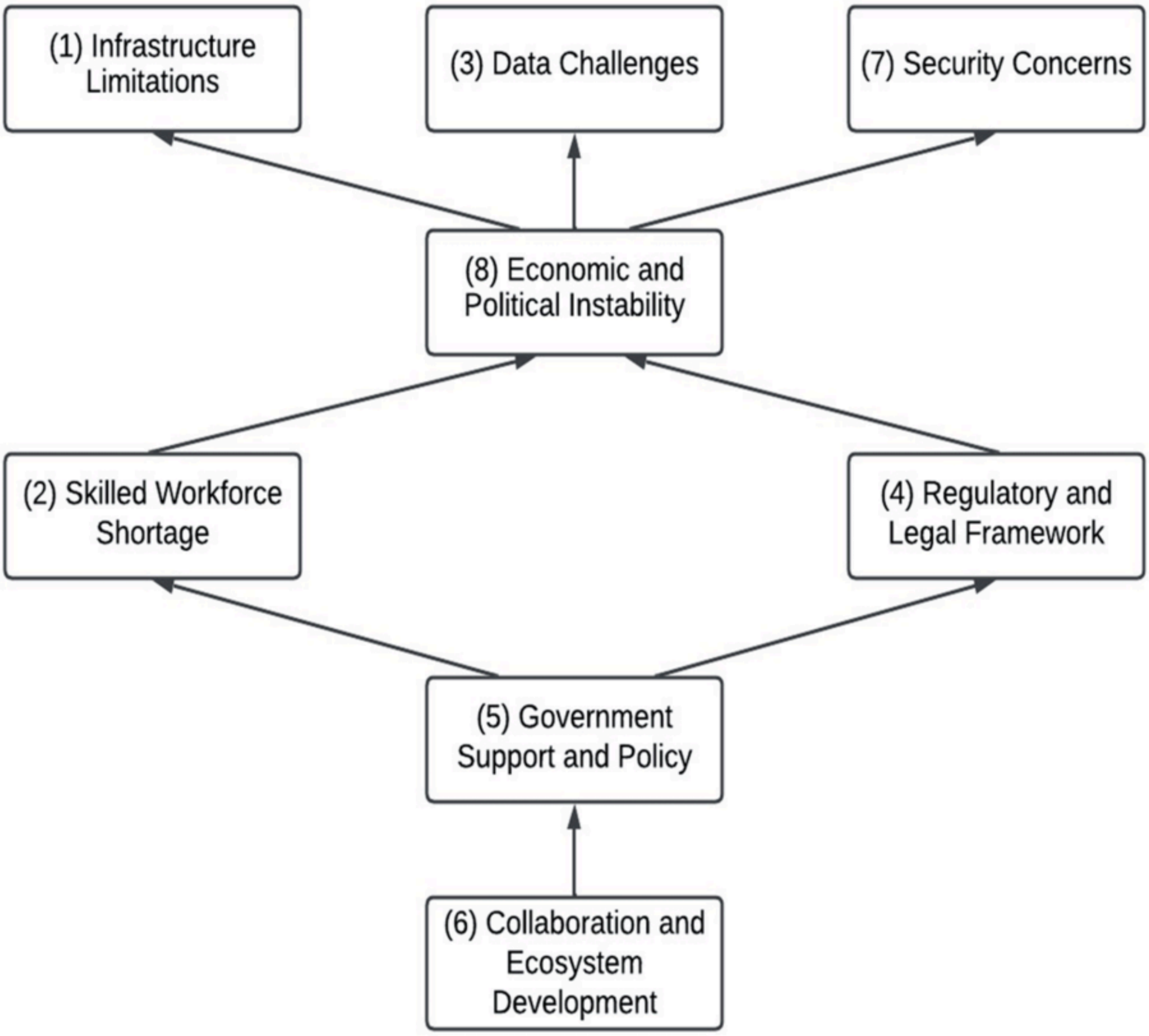

FIGURE 3: ISM-based Model of Barriers to Adoption of AI

Source: Author. ISM, Interpretive Structural Modeling; AI, artificial intelligence

Fuzzy MICMAC analysis

Fuzzy MICMAC analysis was then performed to categorize these barriers in four quadrants, as shown in Figure 4.

Autonomous Barriers (Segment I)

This quadrant comprises elements characterized by both low driving power and low dependence. They are termed autonomous barriers due to their relatively isolated nature within the system, with only a limited number of connections that can be quite robust. The study found none of the barriers in this segment, which means that every barrier examined in the research is somehow crucial and plays a substantial part in the implementation of AI in the supply chain in Pakistan.

Dependent Barriers (Segment II)

This quadrant comprises elements characterized by weak driving power but strong dependence. These obstacles are known as dependent barriers. Most of the barriers fall in this quadrant, suggesting that these factors are outcomes of other systemic issues. Infrastructure Limitations (Barrier 1), Skilled Workforce Shortage (Barrier 2), Data Challenges (Barrier 3), Regulatory and Legal Framework (Barrier 4), and Security Concerns (Barrier 7).

Linkage Barriers (Segment III)

The quadrant (III) incorporates barriers that have strong driving power and strong dependence. They are named as linkage barriers since they are unstable. But any action of these barriers will affect others and, in fact, provide feedback to themselves. Only one barrier i.e. Economic and Political Instability (Barrier 8)

Independent Barriers (Segment IV)

This quadrant consists of elements that possess a robust driving force while dependence power is low, ranking as the fourth group (IV). These are referred to as independent obstacles. The findings of the study depict barriers such as Government Support and Policy (Barrier 5) and Collaboration and Ecosystem Development (Barrier 6) that belong to this group. These independent barriers influence all other barriers and act as significant barriers for AI implementation.

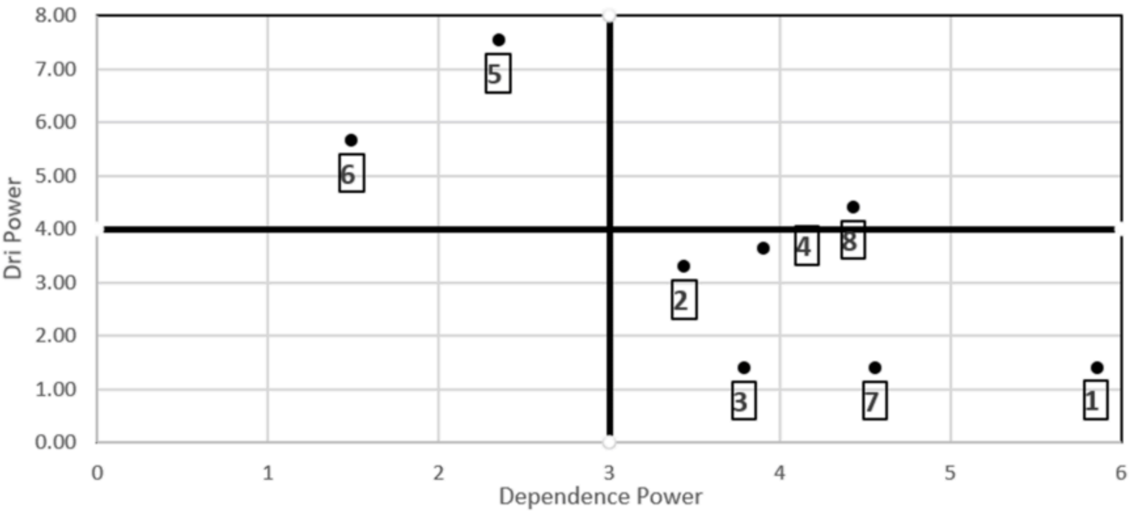

FIGURE 4: MICMAC Analysis of Barriers

MICMAC, cross-impact matrix multiplication applied to classification

Discussion

Recommendations

To address these issues, investment in digital infrastructure and collaboration between governments and the private sector must be made to respond to these challenges (Younus and Zaenuri, 2024). Financial incentives and educational initiatives to reduce costs and increase awareness can drive adoption. If these interdependent barriers are dismantled, the full power of AI could be released and could enable more optimized and resilient supply chains. Addressing these issues will require regulating data practices, investment in infrastructure, portraying strong legal frameworks, and increasing understanding of ethical practices through education. Some potential solutions include: Another important consideration for participants wanting to succeed in developing a resilient supply chain ecosystem is the need for cooperation between countries, businesses, and stakeholders. Moreover, targeted education and training investments, upskilling and reskilling programs, and talent retention policies such as career advancement opportunities and competitive salaries, are of great importance for building a resilient workforce to support the advancement of AI-enhanced SCM. Another way to address these ethical challenges is by promoting public awareness of AI technologies and their issues through awareness campaigns and education programs (Pedro et al., 2019). By engaging multiple stakeholders, policymakers can provide appropriate regulations that stimulate innovation and meet the needs of society. The lack of collaboration between academia and industry, as well as insufficient support for startups, keeps both sectors stagnant, which, in turn, inhibits technological progress and ecosystem dynamism. To address this, collective action is required. Joint research initiatives, skill development programs, and supportive policies should be established with collaboration from governments, academia, and industry stakeholders. Furthermore, improving the ecosystem with funding, grants, tax incentives, and innovation hubs to promote entrepreneurship will also promote supply chain resilience and sustainability. Furthermore, a standardized framework and awareness through educational initiatives should be developed by governments and Industry leaders. The strong collaboration is crucial for building robust, secure systems that enable the innovation and resilience of AI-based supply chain systems (Wu et al., 2025). The establishment of public-private partnerships may enhance cross-sector collaboration, driving sustainable development that provides a stable foundation for innovation in AI-driven supply chains and long-term growth levers.

Implications

The implications of these findings are twofold. Theoretically, our research underscores the systemic nature of AI adoption challenges in supply chains. Traditional approaches that view barriers in isolation fail to capture the interdependencies that our ISM and fuzzy MICMAC analyses reveal. Instead, the hierarchical structure suggests that any attempt to integrate AI must adopt a holistic perspective, addressing not only immediate technical constraints but also the broader ecosystem that supports AI implementation. The results indicate that the success of AI integration is not merely a function of technological readiness but is equally dependent on supportive policies, collaborative networks, and strategic industry-academic-government partnerships. From a managerial perspective, our study provides a clear roadmap for practitioners and policymakers. First, it is essential to prioritize the resolution of independent barriers - namely, enhancing Government Support and Policy and fostering Collaboration and Ecosystem Development. For instance, government bodies need to develop comprehensive regulatory frameworks and propose economic incentives, likewise, grants or tax breaks, to encourage investments in digital infrastructure and AI technologies. Simultaneously, there must be a concerted effort to build a collaborative ecosystem that bridges the gap between academia, industry, and government. Such collaboration can facilitate knowledge sharing, joint research initiatives, and the development of standardized practices for data management and cybersecurity. Furthermore, addressing the operational barriers requires targeted interventions. Investments in robust digital infrastructure, including reliable internet access, secure data storage, and modern power sources, are critical for overcoming Infrastructure Limitations. In parallel, initiatives to improve data quality - through better data collection practices and inter-departmental data sharing - will help mitigate Data Challenges. Equally important is the need to enhance cybersecurity measures to address the pervasive Security Concerns, which, if unaddressed, could compromise both operational integrity and stakeholder trust.

Another managerial implication pertains to the skilled workforce shortage. The study highlights a significant gap in the availability of AI talent, ranging from data scientists to technical support staff. This shortage is exacerbated by a misalignment between industry requirements and the skills taught in educational institutions. Addressing this gap requires a dual approach: investing in comprehensive training programs to upskill existing employees and forging stronger partnerships with academic institutions to ensure that future graduates are better prepared for the demands of AI-driven supply chains. The results also illuminate the role of economic and political instability, which, though classified as a downstream barrier, cannot be ignored. Fluctuations in currency, inflation, and energy shortages directly impact the financial feasibility of implementing advanced technologies like AI. Therefore, managers must adopt strategies that not only optimize operational efficiency but also build resilience against such macroeconomic uncertainties.

Limitations and future research directions

Regardless of the valuable insights yielded by this research, various limitations must be acknowledged, which in turn pave the way for future research directions. One of the primary limitations arises from the reliance on ISM and fuzzy MICMAC analysis methodologies, both of which are fundamentally dependent on expert judgments (Dube and

Gawande, 2016). Although these methods allow for the systematic exploration of interrelationships among the identified barriers, they are inherently subjective and may be influenced by the biases and perspectives of the selected experts. This subjectivity is compounded by the relatively small sample size of experts involved in this study, potentially limiting the generalizability of the findings across the diverse contexts of AI integration in SCM within Pakistan. Furthermore, the study's focus on barriers specific to Pakistan's supply chain environment might not fully capture the broader dynamics applicable to other developing economies, thereby necessitating comparative studies that examine similar challenges in different geographical and economic settings. Another limitation is the cross-sectional nature of the analysis, which offers a snapshot of the barriers at a particular point in time but does not account for the evolving nature of technology adoption and the dynamic interplay of these barriers over time. As AI and digital infrastructure continue to advance rapidly, the relevance and intensity of the identified barriers may shift, making longitudinal studies essential to understanding these temporal dynamics.

Additionally, while the study offers an inclusive overview of infrastructural, regulatory, workforce, data, and security challenges, it does not completely explore the potential moderating effects of external factors like market conditions, global economic trends, or cultural influences, which could play a critical role in either exacerbating or mitigating these barriers. Future research could also investigate the impact of training programs and educational initiatives on alleviating the skilled workforce shortage, exploring how collaborative efforts between academia, industry, and government can foster a more robust talent pipeline to support AI-driven supply chain initiatives. Finally, while this research has provided a structured framework for understanding the barriers to AI implementation, further work is needed to operationalize these findings in practical, actionable strategies that organizations can adopt to foster digital transformation. Future studies might consider developing decision-support tools or frameworks that can guide practitioners in prioritizing and addressing the most critical barriers based on their specific contexts.

These findings align with the Technology-Organization-Environment (TOE) framework, which emphasizes the critical role of external and institutional factors in technology adoption, and with Institutional Theory, which highlights the influence of government support, legitimacy, and ecosystem collaboration on organizational behavior. They also refine prior applications of TAM/UTAUT in supply chain contexts by showing that perceived usefulness and ease of use are often secondary to broader systemic enablers in resource-constrained environments. Thus, this study extends existing theory by demonstrating that in emerging economies, the institutional environment, rather than organizational readiness alone, determines the pace and success of AI adoption.

Conclusions

The results of our study reveal a complex and interconnected set of barriers that hinder the effective integration of AI in SCM in Pakistan. We identified and hierarchically organized eight critical barriers, shedding light on both their individual impacts and their interactions within the broader system. The ISM analysis provided a structured hierarchy of barriers, demonstrating that foundational issues such as Infrastructure Limitations, Data Challenges, and Security Concerns form the operational base of the system. These barriers are primarily technical and logistical in nature. They manifest in inadequate digital infrastructure, insufficient data quality and availability, and weak cybersecurity measures, all of which directly obstruct the smooth implementation of AI systems in supply chain operations. The ISM results indicate that these operational barriers, while critical, are influenced by higher-level factors. A notable insight from the ISM is the positioning of Collaboration and Ecosystem Development (Barrier 6) and Government Support and Policy (Barrier 5) at the top of the hierarchical structure. These independent barriers exhibit strong driving power with relatively weak dependence, as confirmed by the fuzzy MICMAC analysis. In the fuzzy MICMAC model, barriers are categorized into four segments: (1) Autonomous, (2) Dependent, (3) Linkage, and (4) Independent. Our analysis found that while most barriers, such as Infrastructure Limitations, Skilled Workforce Shortage, Data Challenges, Regulatory and Legal Framework, and Security Concerns, fall into the dependent cluster, they are outcomes of or significantly influenced by the independent barriers. The independent barriers, particularly Government Support and Policy and Collaboration and Ecosystem Development, exert substantial influence over the entire system. Their robust driving power suggests that addressing these barriers can trigger a cascading effect, alleviating several other systemic challenges.

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The findings of this study are consistent with global research identifying infrastructure limitations, data quality issues, workforce shortages, and regulatory uncertainty as critical barriers to AI adoption in SCM. However, our results extend the literature by showing that in the context of Pakistan, two barriers - Government Support and Policy, and Collaboration and Ecosystem Development - exert the strongest driving influence on all others. This contrasts with studies in developed economies, where technological and organizational readiness often emerge as the dominant drivers. The prominence of policy and collaboration in Pakistan reflects the institutional voids typical of developing economies, where weak regulatory frameworks and limited industry-academia linkages inhibit digital transformation.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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