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Key Variables Influencing Artificial Intelligence (AI) Implementation In Supply Chain Management (SCM): An Empirical Analysis On Smes

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ABSTRACT

This study seeks to ascertain the principal elements influencing the application of Artificial intelligence (AI) and how the application of AI affects supply chain management (SCM) performance. During the industrial development period, the use of new technologies in supply chain management is important. A more thorough analysis of the problems with supply chain, AI implementation will offer a more unbiased viewpoint on the difficulties and advantages of integrating AI into SMEs' supply chain management. To achieve the research objectives, representative factors for variables were identified and the acceptability of the study sample was evaluated utilizing the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphere city. Regression Analysis was used to test the proposed hypotheses and to validate the conceptual model.

The results indicated that the Managerial Support (MS), Competitive Pressure (CP), Government Support (GS), Vendor Partnership (VP), Compatibility (COMPA), and Relative Advantage (RA) factors are essential in AI implementation. The beta values of all the factors, as indicated by the coefficient, are 0.939[1], 0.367, 0.240, 0.249, 0.190, and 0.161 respectively, which is a reasonable representation of their influence on SCM Performance (SCMP) and AI Implementation (AIIM). The study findings show that variables influence the decision to implement AI applications in supply chain management. Examining these variables is anticipated to have a positive impact and assist strategic planners in developing plans to use AI to support the operational requirements of the company both now and in the future. Research findings have aided companies in realizing the value of artificial intelligence, developing strategies and plans to swiftly transition to digital technology, and streamlining workflows to improve supply chain efficiency.

***Key words**: Artificial intelligence, Supply chain management, Compatibility, Technical Capability, Complexity*

1. INTRODUCTION

Excellence within the chain of supply depends on the company's capacity to incorporate and arrange a comprehensive array of inclusive operations to procure materials or parts, supply the

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products in the required form, and supply them to clients in an era Given growing demand uncertainty, high risk associated with supplies, and increased fierce rivalry. (Mujahid, et. al. 2015). Many top firms have made an effort to improve their sources of information and communicate current data with their partners in the supply chain, as this ability can be increased by improving The precision of the ongoing chain of supply operations (Kahraman et. al. 2014). As a result, supply chain management has shifted from being asset-based to information-based, realizing the growing significance of information for the chain's success. Experts have investigated ways to enhance information management and help decision-makers in the business world (Wong et. al. 2013). Artificial intelligence, which has been around for many years, but hasn't been effectively utilized When it comes to supply chain management, might be one of these techniques. Artificial intelligence has proven to be successful when used in a variety of domains, including robotics, machine learning, data, intelligence, electronic games, semantic modeling, and modeling human performance (data, networks) Bansal et. al. (2018).
However, one unexplored potential using artificial intelligence goes well beyond The theory of supply chain management that is currently in vogue, which necessitates knowledge of intricately linked decision-making procedures and the development of sophisticated knowledge repositories required to resolve typical issues. For instance, the application of codecs streamlines the procedures for expertly reviewing requests collectively and creates a system of experts founded on the principles of the route of selection for selecting the best orders for the storage facility. M. Pagano, et. al. (2019). In an effort to coordinate a number of interconnected stages using various cooperative Planning and forecasting for demand procedures within the chain of supply (García-Alcaraz et. al. 2019).
Through information exchanged between chain partners, it can forecast the demand from the final client. Multiple suppliers and insights from previous forecasting experiences, such as agent-based and expert systems, are helpful in handling many logistics-related concerns (Freitag et. al. 2018) such as inventory control, cooperative demand planning, and storage in the chain of supplies (Levalle et. al. 2018). This is a significant chance to learn about the newest and finest techniques for enhancing supply chain efficiency and performance, as well as to grow the logistics industry and position it as a global hub for logistics in accordance with current supply chain management trends (Saudi Press Agency, (2017).

2. LITERATURE REVIEW

2.1 Artificial Intelligence

AI has grown and collapsed since its launch in 2012 for a variety of reasons. Because of the growing data flow and intricacy that have emerged in the corporate world settings In the course of the last Over the past 20 years, there has been a surge in interest in and use of AI throughout numerous industries (Scholten et al., 2015). In light of present requirements and long-term objectives, the possibilities of artificial intelligence numerous business operations is being investigated. A network of computers with artificial intelligence (AI) can mimic human intellect and make decisions about how to address a business problem (Huang et. al. 2018). Artificial intelligence (AI) has the potential to assist companies in producing the best products possible by quickly determining expectations from customers, observing the market, utilizing failure modes, optimizing supply chains, both internal and external, and fostering a workforce that is more innovative thanks to automation of repetitive tasks (Jabbour et al., 2020). AI has been consistently embraced by a range of industries, e-commerce and manufacturing, among others, to handle supply chain issues. During COVID-19, the majority of supply chains underwent a new degree of resilience testing as things were required to manage ever more complex tasks (Zouari et al., 2021). In the current corporate climate, customers want networks of supplies to offer both dependability and personalized solutions. AI has been used to create a system with the ability to recognize client profiles and offer customized products without

jeopardizing security or privacy. In conclusion, supply networks and establishments that do not identify and leverage Utilizing AI in their operations runs the danger of achieving the required resilience of the supply chain in the dynamic business market that may arise due to COVID-19-like scenarios. This is because Utilizing AI is growing at a quick speed.
A branch of artificial intelligence called "expert systems," sometimes referred to as "knowledge-based systems," focuses on creating software that allows computers to carry out jobs that have traditionally been completed by people using the help of specialized training and supply chain management knowledge (Pournader et al., 2021). To get the best results from AI Expert systems in supply chain management techniques for example, fuzzy, rule-based, and frame-based and hybrid approaches can be employed in combination with one another (Zarbakhshnia et al., 2018). Jakupović et al. (2014) found that expert systems function exceptionally effectively in domains where human intellect may be properly arranged.

2.2 Compatibility

The term "compatibility" refers to the level of development and the ability to treat customers with respect and experience. Simultaneously, compatibility has a favorable effect on the intended implementation of false insights in SMEs, or small and medium-sized businesses (A Kumar et. al. 2021). According to Oliveira et al. (2014), compatibility is a key factor in determining the acceptance of innovations. This pertains to the degree of the ability of innovation to offer experience and worthwhile adhering to the requirements of possible users (Rogers, 1995). The DOI theory states that adoption of innovations has a favourable correlation with their suitability for a given set of circumstances and experiences. A high degree of compatibility may lead to adoption that is more favoured. Stated differently, adoption occurs more quickly with more compatibility (Wu et al., 2007). Workers probably utilize AI technology if it is deemed in line with the methods of work used now, even though the company will need to produce some modifications. This is because incompatibilities typically necessitate significant process adjustments, which can be difficult to adopt and require a lot of learning. Massive amounts of data are needed for AI technologies, particularly machine learning (Huang et al. 2006). AI technologies can be integrated with a company's data resources since they allow the company to assess the data it collects and stores. Artificial intelligence (AI) technologies are more in harmony with network both the software and hardware in businesses than current technological. As the anticipated cost and time associated with implementing AI technology will be reduced if it is compatible with current IT settings.
H1: Compatibility (COMPA) has a worth mentioning positive influence on AI Implementation (AIIM)

2.3 Relative Advantage

According to Souma et al. (2020), relative advantage refers to the advantages of implementing AI at the company level. The goal of obtaining fake insights in SMEs is positively impacted by comparative advantage (Souma et al., 2020). Businesses can reduce operating expenses by implementing AI innovation, which increases revenue (Tatjana et al. 2021).
As stated by Yang et al. (2013) relative advantage, which measures how much an invention is regarded as superior to the method it takes the place of. According to Rogers (2003), a company's intention adoption of new technology is impacted by how valuable they consider innovation to be. As a result, new technologies are more likely to be accepted if they offer distinct advantages that increase strategic and operational effectiveness (Greenhalgh et al., 2004). Put another way, new technology will spread more quickly if its apparent relative advantage is greater.
Businesses are driven to implement cutting-edge information technology in order to enhance their business operations when confronted with intense market rivalry in a rapidly evolving

business environment. AI is capable of deep learning, sophisticated computing, and cross-border integration (Russell et al. 2016). Artificial Intelligence has the ability to significantly contribute to the mainstream adoption of innovative services. Massive data and AI technology together will undoubtedly provide businesses with innovative solutions and a competitive edge. According to El Khatib et al. (2019), artificial intelligence has been used in customer service chat bots, voice as well as voice services for users, and network procedures that are automated. These programs enhance client experiences, boost efficiency, decrease operating costs, and improve service quality for businesses. Employees can fully grasp the benefits of artificial intelligence (AI) if their employer uses education or training to make them aware of how fundamental NLP (natural language processing) technologies are examples of AI and profound understanding can save expenses and increase efficiency. Once people are more aware of the benefits of AI, they may embrace these developments and take an active part in them. This suggests the following theory.

H2: Relative Advantage (RA) has a worth mentioning positive influence on AI Implementation (AIIM)

2.4 Managerial support Top management support.

The phrase "best administration support" is a term used to describe the involvement of a high-level pioneer in IS/IT utilization. When expressing a strategy, allocating capital reserves, and allocating resources, top administration commitment can have a favourable impact on underused innovation appropriation (Praveen et al., 2020). Without excellent senior leaders' organizational support inside the company and infrastructure support, the selection of fake insights is not possible (Souma et al., 2020).

Any significant organizational transformation must include the commitment of managers since it directs the distribution of assets and service integration (Co et al., 1998). Researchers discover that management Support plays a big part in both the use of IT (Chong et al., 2009) and the implementation of IS (Müller et al., 2012). For instance, Thong (1999) discovers that an organization's senior executives' attributes have an impact on the adoption of IT within the company. Higher-level managers who have the authority to distribute organizational resources have an influence on the adoption of new ideas (Hage et al. 1973). According to Elbanna (2013), for a project to succeed Management assistance is required to continuous and consistent all during the project's execution. The rationale is that managers, particularly those in higher positions, have the authority to assign important staff members to supervise particular projects and provide ample funding and other resources to them (Willis et al., 1984). Conversely, a project may experience a shortage of managerial assistance (Wixom et al. 2001).

AI tools have the potential to transform entire organizations. Firms may be significantly impacted by such changes. Manager support is crucial for AI applications to coincide with the strategic goals of organizations, as managers play a significant influence in the adoption of IT. Managers are able to decide how to apply AI when they have a thorough understanding of the technology and the activities that the entire company is involved in. Furthermore, managers are more likely to exist active and prepared to commit materials for the execution of AI applications once they are recognized as high priority (Nah et al., 2001). It is imperative that supervisors possess a concrete and perceptive comprehension of artificial intelligence (AI) in order to facilitate the most productive working relationships with their suppliers.

H3: Managerial Support (MS) has a worth mentioning positive influence on AI Implementation (AIIM) in SCM

2.5 Cost

This variable describes how adopting technology too quickly will have expensive results. Because it is simple to raise the expenses of hardware equipment, operation, and maintenance, technology use processes must be controlled (Lin et al., 2016). In this study, "cost" refers to cost-effectiveness, the state in which a technology adoption's costs are comparatively lower than its benefits. Nevertheless, despite declining costs for hardware and software, cost is still a noteworthy deterrent to the acceptance of novel technological innovations (Puklavec et al. 2017). The requirement to teach end users in order to guarantee that the technology is properly applicable to MSMEs accounts for the high cost of adoption.

Previous research used a variety of methods to argue the financial and economic aspects of an innovation (Hameed et al., 2012). According to Premkumar et al. (1999), we define cost in relation to cost-effectiveness when the advantages of implementing modern technology outweigh the expenses associated with it. The cost factor is no longer a barrier for SMEs to embrace, but it is still a significant obstacle. embracing innovations in IT because of advancements in IT development, the availability of off-the-shelf solutions, and declining software and hardware costs (Premkumar et al. 1999). Furthermore, according to Iacovou et al. (1995), of the crucial factors impeding IT for small enterprises development is cost. Consequently, prior to choosing Businesses usually use IT innovations to implement new ideas. Weigh the costs and advantages (Premkumar et al. 1999). Costs have been shown to significantly affect both of them the acceptance and use stages, which are the next phases of adoption (Chong et al. 2012). This could be clarified by the significance Companies focus on reducing expenses and, consequently, by their willingness to take advantage of modern IT to do so (Tung et al., 2005). A possible argument could be that companies want for a sustained rather than merely temporary return on their IT investment savings (Chong et al., 2012).

H4: High Cost (COST) has a worth mentioning negative influence on AI Implementation (AIIM) in SCM

2.6 Technical Capability

Technical capability is the term used to describe the tangible resources include data, networking, and computer hardware, that are necessary to implement innovations (Aboelmaged, 2014). According to Wang et al. (2016), it also symbolizes the group of resources that a company has available to it for the purpose of giving itself a scalable and adaptable base for business applications. Collaboration, IT development, and technical expertise techniques, and utilization methods that is able to successfully incorporate new technologies are examples of intangible assets that fall under the category of proficiency with technology (Garrison et al., 2015). It is a crucial element influencing the adoption of IT (Garrison et al., 2015). According to Orut Puklavec et al. (2018), preparedness of organizations is the extent to which a business has ready its sources to accept new technological applications. Small and medium-sized firms can simply and effectively accomplish their goals when they plan thoroughly. In particular, there is enough financial resources, expertise, and knowledge to be prepared to deploy artificial intelligence (Anjali et al., 2021). Robust technical capacity lowers integration complexity and enables the IT department to quickly and effectively offer AI technology. A company can successfully implement AI applications if it can easily integrate new AI technologies into its current infrastructure and supply technical solutions. The more quickly a company can cut costs and strategically deploy resources to ensure effective adoption, the more adept it is at integrating AI new technology into the current IT architecture. A company must comprehend the technological, competencies, and assets required to fully utilize AI, regardless of whether it develops its own tools or platform for AI internally or outsources the development to suppliers or partners.

H5: Technical Capability (TC) has a worth mentioning positive influence on AI Implementation (AIIM) in SCM

2.7 Competitive Pressure

The pressure of competition is what propels technological innovation. In order to compete in the market, adopting new technology is frequently strategically required (Lippert et al. 2006). Competitive advantages held by businesses are transient rather than permanent. Porter et al. (1985) note that IT innovation has the power to modify the competitive landscape, industry structures, and rules of engagement. It can also create new opportunities for competitive advantage.

One external hazard that pushes a company to implement a breakthrough by jeopardizing a competitive advantage is competition (Danping et al. 2016). Artificial Intelligence (AI) has the ability to foster innovation and present novel opportunities for both individuals and corporations. The capacity to apply AI to improve customer experience and Making decisions has an influence on the acceptance of AI (Souma et al., 2020).

According to Mansfield et al. (1977), intense market rivalry encourages the quick spread of IT advances. One important element affecting the uptake of IT is competition pressure (Gibbs et al., 2004). Often, an organization's approach to be competitive in the market is to adopt new technologies. Businesses experience pressure if rivals use specific new technologies. In order to stay competitive, they frequently implement new technologies right away (Oliveira et al. 2008). Businesses that effectively implement novel Artificial intelligence technology In order to improve their services, will secure a competitive advantage over their rivals. Consequently, businesses employ AI applications and technologies due to pressure from the competition.

H6: Competitive Pressure (CP) has a worth mentioning positive influence on AI Implementation (AIIM) in SCM

2.8 Government Support

In addition to external pressure, one of the things that businesses must consider is the government (Anjali et. al. 2021). Regulatory difficulties relate to the government's support in encouraging the implementation in AI technologies at the level of the organization in this study. In the context in AI, different governments have different policies.

An essential factor in promoting IT innovation is government policy (Mogel et al. 2003). According to Huang et al. (2001), laws have the power to erect or take out obstacles to the commencement of new Systems and IT, and the government can promote the spread of IT. The government could set new regulations for the development of new technologies as well as strategies and policies that encourage the commercial applications of emerging technology. According to Stoica et al. (2005), adopting Modern technology is a difficult procedure, and government frameworks play a crucial role. AI stands for artificial intelligence. Revolutionary technological that touches on a wide variety of topics, including social ethics, privacy, and security. AI hence need appropriate laws or regulatory frameworks. This indicates that as AI technology develops quickly, legal, security, ethical, and governance issues present more difficulties and conflicts. According to Agrawal et al. (2018), government backing for artificial intelligence creates a favourable atmosphere and will encourage the spread and effects of AI. In order to receive funding and resources to advance their work, AI providers must have positive relationships with the government.

H7: Government Support (GS) has a worth mentioning positive influence on AI Implementation (AIIM) in SCM

2.9 Market Uncertainty

Although outside of a company's control, market variables including product demand, level of competition, and customer loyalty can have an impact on how well a company performs (Hao et al. 2018). Any commercial market has a great deal of uncertainty, as we all know. Opportunity and risk are mutually exclusive. Competitive advantages will go to whoever can identify particular chances in an unpredictable market. To take advantage of the prospects presented by AI, numerous nations and institutions have published development strategies or relevant policies. According Regarding China's Development Plan for New Generation Artificial Intelligence, country's AI core industry is expected to generate over 1 trillion yuan in revenue by 2030, pushing related industries to generate over 10 trillion yuan. This suggests that AI offers a sizable market and enormous potential (Creemers et al. 2017). Even though there is a lack of qualified professionals and technicians in the field and many AI technologies and the field of applications is very young. AI has already proven to be very viable and is giving businesses greater opportunity to compete. Chat bots and voice assistants for customer support, for instance, can help businesses save labor expenses and enhance productivity. More than 70% of customer inquiries have already been handled by Vodafone's chat bot TOBi (Vodafone et al. 2017). Furthermore, AI technologies are the only ones capable of handling certain complicated tasks like fact detection and fingerprint identification. Businesses can use AI technologies to draw in new clients and strengthen their relationship with current ones. Although there is a great deal of commercial potential for AI applications, the current application landscape is still being investigated. Even if a lot of applications are still in the research and development stage, astute businesses are nevertheless entering the AI space. This suggests the following theory.

H8: Market Uncertainty (MU) has a worth mentioning negative influence on AI Implementation (AIIM) in SCM

2.10 Vendor Partnership

Generally speaking, a company lacks some of the technical and transformative expertise needed to manage advances like artificial intelligence. Therefore, because many businesses are not familiar with AI technologies, AI's implementation in enterprises is typically linked to IT suppliers and cooperative partners. As stated by Assael et al. (1984), vendor participation can have a major impact on how quickly innovative products are adopted and diffused. One of the main elements affecting the uptake of innovations is vendor partnership, according to empirical evidence (Ahmadi et al., 2015). Nowadays, a lot of businesses get the great majority of their network and IT technologies from suppliers who adhere to standards. However, these suppliers aren't the greatest places to get AI technology. In the realm of AI, suppliers hold a special and noteworthy position. In order to train their AI technologies, vendors require enormous amounts of data, many of which contain private customer data. Thus, suppliers sometimes are not able to offer plug-and-play AI systems; Rather, they need to work closely with companies (their clients). in order to provide AI instruction for both before and following the implementation. To expedite the implementation of AI technology, companies need to standardize the data gathering and administration process in order to work with top providers of artificial intelligence. Additionally, the fundamental components of AI are models and algorithms. Since many businesses lack expertise in algorithms, they must provide an open platform where vendors may work together to develop AI programs. As a result, vendor relationships have a big impact on how AI is adopted. For instance, China Unicom collaborates with high-tech businesses Baidu, Iflytek, Alibaba, and Tencent to create AI applications, such as intelligent services and smart products. An open-source AI platform is being developed by Tech Mahindra and AT&T together. A collaborative AI/5G lab between China Mobile and Nokia was established to investigate 5G network applications utilizing AI. Such a type of collaboration has made full use of the beneficial resources in each of their domains and has worked to further the use of AI through complementary technologies and resource replacement. As a result, AI suppliers are able to heavily push AI applications.

H9: Vendor Partnership (VP) has a worth mentioning positive influence on AI Implementation (AIIM) in SCM

2.11 Complexity

According to Souma et al. (2020), Complexity is negatively correlated with the goals of AI selection, usage, and mechanization throughout the supply chain risk management (SCRM). The use AI's use to supply chain management (SCM) necessitates highly skilled personnel, which adds a significant layer of complexity to this invention. According to Yang et al. (2013), The level of intricacy of an innovation is its thought to be particularly challenging to comprehend and use. Put differently, complexity refers to the hindrances or impediments to the adoption of AI. The likelihood of technology adoption increases with its ease of integration into corporate operations (Oliveira et al., 2014). The inexperience, lack of IT specialists and technological know-how, high cost, and length of time are the main causes of AI's complexity. The characteristics of AI imply that the largest obstacle to its adoption. Prior research indicates that the degree of IT maturity has a major influence on the tactical choices made by businesses when implementing and acquiring IT/IS. Firms are more knowledgeable about the application of a new technology if it is mature. Businesses are more inclined to implement new if they have faith in their capacity to work with technology vendors (Huang et al., 2001).
H10: Complexity (COMPL) has a worth mentioning negative influence on AI Implementation (AIIM) in SCM

2.12 Impact of AI on SCM Performance

Achievement evaluation is crucial due to the fact that teaches companies how to better fulfil their clients and meet their extended goals. Evaluating the degree to which demands are satisfied, and resources are used efficiently is necessary to reaching the intended degree of contentment among clients. An assessment of the supply chain considers the interdependencies of all of the businesses engaged in the chain instead of focusing on the execution of a single organization. It influences understanding of the overall system by providing context. Human behaviour, and exposes The efficiency of supply chain participants and stakeholders. The creation and utilization of performance metrics is essential to management. Using performance measuring instruments encourage transparency and deep supply chain understanding. Keeping an eye on crucial metrics, metrics like lead time, fill rate, and on-time performance can be used to gauge the supply chain's efficiency (Yu et al., 2017).

According to the studied literature, supply chain management can make use of a number of technological advancements, such as artificial intelligence (AI). Stock management may experience a revolution as a result of AI-powered systems' capacity to handle massive data volumes. Huge these intelligent systems can evaluate and understand datasets fast, giving supply and demand planners immediate, actionable insights (Ben-Daya et al., 2019). These AIs' complex algorithms allow them to be able to develop accurate forecasts about upcoming trends in seasonality and customer. An overview of the use of AI in supply chain management was given by Stoyanov (2021). According to his paper, AI gives businesses an autonomous supply chain that has the capacity to develop into a self-defining, self-aware, and self-managing system.

All things considered, artificial intelligence (AI) can assist businesses in optimizing their supply chains through cost savings, increased productivity, and higher-quality goods and services.

H11: AI Implementation (AIIM) has a worth mentioning positive influence on SCM Performance (SCMP)

3. CONCEPTUAL FRAMEWORK

The proposed model includes and represents the relationship between influencing and dependent factors as Compatibility (COMPA), Relative Advantage (RA), Managerial Support (MS), Cost (COST), Technical Capability (TC), Competitive Pressure (CP), Government

Support (GS), Market Uncertainty (MU), Vendor Partnership (VP), Complexity (COMPL), AI Implementation (AIIM), SCM Performance (SCMP) (Figure 1).

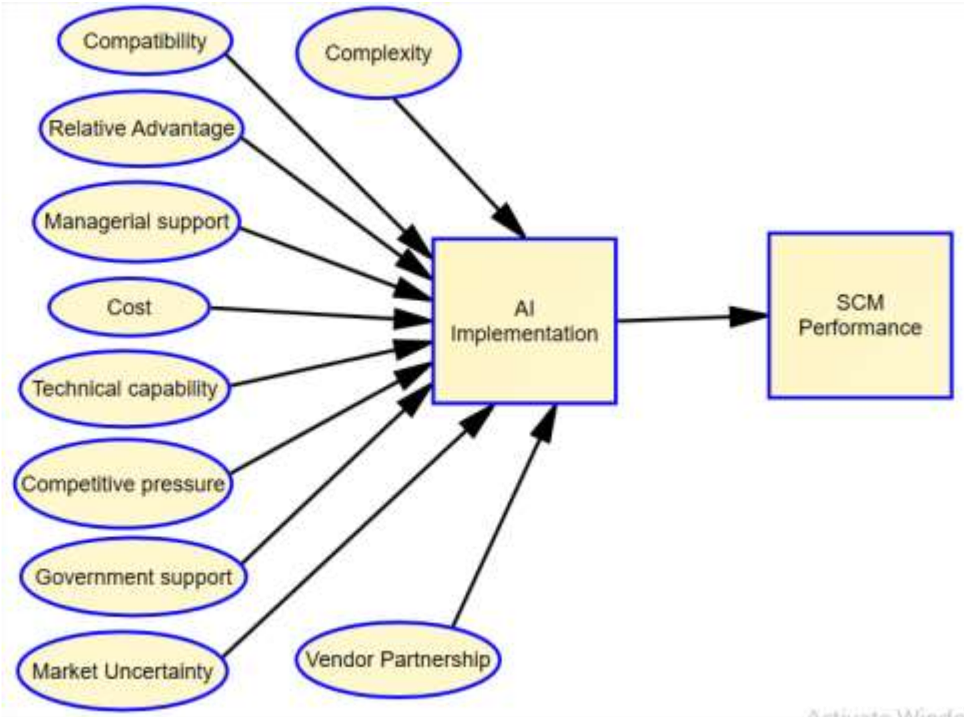

Figure 1: the relationship between influencing and dependent factors influencing SCM

4. RESEARCH OBJECTIVE

- To determine the principal elements influencing the application of Artificial intelligence
- To offer a conceptual framework pertaining to important factors affecting artificial intelligence and how the application of AI affects SCM performance.
- The suggested framework will be validated by empirical study.

5. RESEARCH METHODOLOGY

The primary goal of quantitative Investigating is numbers. It makes use of data and statistical analysis to highlight important market and company information. A survey questionnaire was created as a data gathering tool for a quantitative data-based inquiry. The questionnaire has been carefully designed to fulfil the goals of the research. A 5-point Likert scale was employed to assess the degree of agreement among the participants (Babakus, et al., 2003). Diverse age groups participated in a pilot study to assess the data collection technique. Based on the findings of the pilot study, we modified the instrument and conducted a survey to test the research model. The study sample consisted of experienced users who had dealt with the application of AI at least once. The survey had 624 valid responses.
Cronbach Alpha coefficient was employed as the basis for the reliability assessment that was used to process the study's data. Regression Analysis was used to test the proposed hypotheses and to validate the conceptual model.

6. RESULTS AND ANALYSIS

6.1 Demographic Profile

The respondent's demographic characteristics were evaluated using descriptive demographic statistics expressed as a percentage, proportion, and frequency of occurrence. The study sample consisted of respondents who had dealt with the use of AI once or more. A systematic questionnaire was used to gather data between April 2022 and May 2023. Using a combination of random and selective sample methods, 650 respondents were given questionnaires. Of those, 596 were found to be error-free and perfectly completed. Upon close inspection, 91.69% of responses are deemed to be of good quality. Table 1 provides socio-demographic details about the individuals. Of the 596 respondents, there were significantly more men (502, 84.2%) than women (94, 15.8%); the majority of the men (167, 28.0%) were in the 30- to 39-year-old age range, and 255 (42.8%) had professional education and were making over 30,000 rupees (218, 36.6%).

Table 1. Descriptive Statistics of Demographic Profile

		Frequency	**Valid %**
Gender profile	Male	502	84.2
	Female	94	15.8
Age profile	20-29 years	82	13.8
	30-39 years	167	28.0
	40-49 years	113	19.0
	50-59 years	143	24.0
	60 years and above	91	15.3
Highest education level	Bachelor Degree	74	12.4
	Masters Degree	155	26.0
	Professional Education	255	42.8
	Other	112	18.8
Income	10,000- 20,000	133	22.3
	20,001- 30,000	206	34.6
	30,001- 40,000	218	36.6
	More than 40,000	39	6.5

6.2 Exploratory Factor Analysis

For the exploratory factor analysis (EFA), the PCA method for conforming constructs was utilized. According to Hair et al. (1998), factor loading of 0.40 is considered more noteworthy, and loading of 0.50 or higher is considered very significant. It is believed that a factor loading of less than 0.30 meets the minimum requirement. For factor loading, the current study has used a cut-off point of 0.50. Table 2 shows the results of the factor analysis.

KMO Values ranging from 0.5 to 1.0 generally indicate the significance of factor analysis for the provided data. The correlation between the variables' items is displayed by the Bartlett's Spiral City Test results. The significance level of the test result is shown. Very small values (less than 0.05) suggest a strong likelihood of meaningful relationships between the variables. If the value is more than approximately 0.10, factor analysis may not be suitable for the given data. The outcomes of these two tests demonstrate that factor analysis makes sense with the available data. In the end, 57 items were confirmed for the final analysis after 6 items with loadings less than 0.5 were removed.

Table 2. Results of Exploratory Factor Analysis

Statement	**Factor**	**KMO Measure**	**Bartlett's Test of Sphericity**	**Items**	**Items**	**Cum**

	loadings	**of Sample Adequacy (>0.5)**	**Chi Square**	**Sig. (<.10)**	**confirmed**	**dropped**	**% of loading**
Compatibility (COMPA) -1	0.904	0.751	1.13213	0.000	4	1	56.081
Compatibility (COMPA) -2	0.741						
Compatibility (COMPA) -3	0.692						
Compatibility (COMPA) -4	0.32						
Compatibility (COMPA) -5	0.854						
Relative Advantage (RA) -1	0.776	0.733	465.087	0.000	4	1	43.865
Relative Advantage (RA) -2	0.792						
Relative Advantage (RA) -3	0.35						
Relative Advantage (RA) -4	0.711						
Relative Advantage (RA) -5	0.664						
Managerial Support (MS) -1	0.26	0.860	2.70123	0.000	4	1	71.483
Managerial Support (MS) -2	0.930						
Managerial Support (MS) -3	0.947						
Managerial Support (MS) -4	0.955						
Managerial Support (MS) -5	0.930						
Cost (COST) -1	0.858	0.736	637.335	0.000	4	0	58.082
Cost (COST) - 2	0.802						
Cost (COST) -3	0.545						
Cost (COST) -4	0.804						
Technical Capability (TC) -1	0.952	0.719	7.26633	0.000	5	0	90.612
Technical Capability (TC) -2	0.948						
Technical Capability (TC) -3	0.952						
Technical Capability (TC) -4	0.958						
Technical Capability (TC) -5	0.949						
Competitive Pressure (CP) -1	0.891	0.838	2.05913	0.000	5	0	72.176
Competitive Pressure (CP) -2	0.910						
Competitive Pressure (CP) -3	0.890						
Competitive Pressure (CP) -4	0.816						
Competitive Pressure (CP) -5	0.727						
Government Support (GS) -1	0.623	0.678	1.43503	0.000	4	0	68.169
Government Support (GS) -2	0.866						
Government Support (GS) -3	0.939						
Government Support (GS) -4	0.840						
Market Uncertainty (MU) -1	0.832	0.773	850.078	0.000	4	1	52.838
Market Uncertainty (MU) -2	0.725						
Market Uncertainty (MU) -3	0.18						
Market Uncertainty (MU) -4	0.674						
Market Uncertainty (MU) -5	0.860						
Vendor Partnership (VP) -1	0.659	0.702	1.53143	0.000	4	0	70.560
Vendor Partnership (VP) -2	0.884						
Vendor Partnership (VP) -3	0.944						
Vendor Partnership (VP) -4	0.846						

Complexity (COMPL) -1	0.903	0.853	2.22623	0.000	5	0	74.227
Complexity (COMPL) -2	0.917						
Complexity (COMPL) -3	0.899						
Complexity (COMPL) -4	0.828						
Complexity (COMPL) -5	0.748						
AI Implementation (AIIM) -1	0.31	0.858	2.71363	0.000	4	1	51.182
AI Implementation (AIIM) -2	0.936						
AI Implementation (AIIM) -3	0.946						
AI Implementation (AIIM) -4	0.951						
AI Implementation (AIIM) -5	0.927						
SCM Performance (SCMP) -1	0.784	0.739	483.171	0.000	4	1	44.392
SCM Performance (SCMP) -2	0.799						
SCM Performance (SCMP) -3	0.21						
SCM Performance (SCMP) -4	0.698						
SCM Performance (SCMP) -5	0.673						

6.3 Reliability Analysis

The internal consistency of the questionnaire has been established by calculating its reliability using Chronbach Alpha. According to Nunally and Bernstein (1994), the minimum alpha value that should be used for new scales is 0.60. If not, an alpha value of 0.70 is typically regarded as the standard for an internally consistent established scale.

Cronbach's alpha was found to be within an acceptable range, meaning that a value greater than 0.7 was chosen as the study's cut-off value. Table 3 shows that the questionnaire's overall Cronbach's alpha value is 0.984, which is quite high and suggests that the research tool was sufficiently reliable.

Table 3 : Results of Reliability test

VARIABLE	Cronbach alpha
Compatibility (COMPA)	0.820
Relative Advantage (RA)	0.722
Managerial Support (MS)	0.957
Cost (COST)	0.740
Technical Capability (TC)	0.974
Competitive Pressure (CP)	0.903
Government Support (GS)	0.843
Market Uncertainty (MU)	0.792
Vendor Partnership (VP)	0.860
Complexity (COMPL)	0.913
AI Implementation (AIIM)	0.958
SCM Performance (SCMP)	0.728
Overall Reliability of the	

Questionnaire	0.984

6.4 Correlatıon Analysis

All of the variables appear to have a significant correlation, according to the results of the independent variable correlation analysis. Significant correlations exist between all 12 of the variables under consideration and the total variables. Each of the independent and dependent variable has a significant relationship with every other factor that was taken into consideration (Table 4). SCMP and RA variables had the highest degree of correlation (0.987), while SCMP and COMPA had the least significant relationships (0.726).

Table 4: Correlations

	COMPA	RA	MS	COST	TC	CP	GS	MU	VP	COMPL	AIIM	SCMP
COMPA	1											
RA	.738**	1										
MS	.911**	.823**	1									
COST	.862**	.794**	.900**	1								
TC	.881**	.802**	.923**	.838**	1							
CP	.869**	.810**	.935**	.847**	.949**	1						
GS	.880**	.751**	.920**	.862**	.890**	.893**	1					
MU	.843**	.818**	.898**	.923**	.868**	.876**	.846**	1				
VP	.865**	.738**	.897**	.835**	.873**	.869**	.965**	.822**	1			
COMPL	.850**	.794**	.912**	.822**	.920**	.966**	.865**	.853**	.897**	1		
AIIM	.899**	.813**	.983**	.881**	.913**	.922**	.902**	.885**	.919**	.940**	1	
SCMP	.726**	.987**	.810**	.783**	.788**	.794**	.741**	.809**	.745**	.805**	.816**	1

**. Correlation is significant at the 0.01 level (2-tailed).

6.5 Regression Analysis

Stepwise regression analysis was utilized to ascertain the predictor-criterion relationship between the independent and dependent variables. The study's objective was to use artificial intelligence to predict the relationship between significant variables and supply chain management.

Using step-wise regression analysis, table 5 and 6 revealed that factors (Compatibility (COMPA), Relative Advantage (RA), Managerial Support (MS), Cost (COST), Technical Capability (TC), Competitive Pressure (CP), Government Support (GS), Market Uncertainty (MU), Vendor Partnership (VP), Complexity (COMPL), AI Implementation (AIIM)), taken under consideration, are considerable predictors of SCM Performance (SCMP). Table 5's R square values of 0.994 and 0.816 show that these variables can account for 99.4% and 81.6% of the variation in AI Implementation (AIIM) and SCM Performance (SCMP). Table 6 displays the regression model's ANOVA values, which indicate validation at a 95% confidence level. The beta values of all the factors, as indicated by the coefficient summary in Table 7, are 0.939 and 0.816, respectively, which is a reasonable representation of their influence on SCM Performance (SCMP) and AI Implementation (AIIM).

Table 5 : Regression analysis

Model	Predictors	Dependent variable	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	COMPA, RA, MS, COST, TC, CP, GS, MU, VP, COMPL	AIIM	0.997	0.994	0.994	0.07624
2	AIIM	SCMP	0.816	0.667	0.666	0.42564

Table 6 : ANOVA analysis

Model	Predictors	Dependent variable		Sum of Squares	df	Mean Square	F	Sig.
1	COMPA,RA, MS, COST, TC, CP, GS, MU, VP, COMPL	AIIM	Regression Residual Total	563.449 3.400 566.849	10 585 595	56.345 0.006	9.6943	0.000
2	AIIM	SCMP	Regression Residual Total	215.111 107.613 322.724	1 594 595	215.111 0.181	1.1873	0.000

Table 7: Regression coefficients table for dependent variables

Model		Dependent variable	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
			B	Std. Error	Beta		
1	Constant COMP	AIIM	0.010	0.010	0.190	1.630	0.003
2	Constant RA	AIIM	0.008	0.008	0.161	1.854	0.000
3	Constant MS	AIIM	0.953	0.013	0.939	72.400	0.000
4	Constant COST	AIIM	-0.018	0.012	-0.014	-1.462	0.004
5	Constant TC	AIIM	0.024	0.011	0.024	2.141	0.003
6	Constant CP	AIIM	0.414	0.027	0.367	15.237	0.000
7	Constant GS	AIIM	0.279	0.026	0.240	10.846	0.000
8	Constant MU	AIIM	-0.018	0.012	-0.014	-1.475	0.001
9	Constant VP	AIIM	0.282	0.025	0.249	11.278	0.000
10	Constant COMPL	AIIM	-0.450	0.024	-0.411	-18.425	0.000
11	Constant AIIM	SCMP	0.616	0.018	0.816	34.458	0.000

6.6 Results of Hypotheses Testing

Eleven hypotheses were first put forth in the conceptual research framework, and as table 8 indicates, all of them have been accepted.

Table 8: Summary of Hypotheses Testing

Hy. No.	Independen tVariables	Dependent Variables	R-Squar e	Beta Coeffi cient	t-value	Sig Valu e	Status of Hypothese s
H1	Compatibility (COMPA)	AI Implementatio n (AIIM)	0.994	0.190	1.630	0.003	Accepted
H2	Relative Advantage (RA)	AI Implementatio n (AIIM)	0.994	0.161	1.854	0.000	Accepted

H3	Managerial Support (MS)	AI Implementation (AIIM)	0.994	0.939	72.400	0.000	Accepted
H4	Cost (COST)	AI Implementation (AIIM)	0.994	-0.014	-1.462	0.004	Accepted
H5	Technical Capability (TC)	AI Implementation (AIIM)	0.994	0.024	2.141	0.003	Accepted
H6	Competitive Pressure (CP)	AI Implementation (AIIM)	0.994	0.367	15.237	0.000	Accepted
H7	Government Support (GS)	AI Implementation (AIIM)	0.994	0.240	10.846	0.000	Accepted
H8	Market Uncertainty (MU)	AI Implementation (AIIM)	0.994	-0.014	-1.475	0.001	Accepted
H9	Vendor Partnership (VP)	AI Implementation (AIIM)	0.994	0.249	11.278	0.000	Accepted
H10	Complexity (COMPL)	AI Implementation (AIIM)	0.994	-0.411	-18.425	0.000	Accepted
H11	AI Implementation (AIIM)	SCM Performance (SCMP)	0.667	0.816	34.458	0.000	Accepted

7. DISCUSSION

The paper aims to look into the application artificial intelligence's effect on performance in supply chain management. AI is becoming more and more used in supply chain management. Demand forecasting, logistics hub management, distribution and transportation, sales, and marketing are just a few of the supply chain management subfields that profit greatly from artificial intelligence (AI). Lean and Agile supply chain performance is something that artificial intelligence can enhance. (AI) through increased flexibility and responsiveness, waste reduction, improved customer satisfaction, and improved teamwork. Notwithstanding the possible advantages, it's crucial to keep in mind that incorporating AI into Supply chain management presents significant moral dilemmas. like data security and privacy and necessitates a significant time and resource commitment. As a result, businesses should carefully evaluate the risks and viability of integrating AI with supply chain supervision before moving forward.

The results of research on the relationship between **Compatibility (COMPA)** and AI Implementation (AIIM) (H1; R-square = 0.994; Beta coefficient = 0.190; t-value = 1.630) verified the presence of a significant positive connection. The outcomes of earlier research that were included in the literature review support this finding Wang et al., 2010). Remarkable is AI's compatibility. compatibility helps the services industry adopt cloud computing. They highlight how different the work practices and Internet-based business strategies of the manufacturing and service industries are from one another.

Based on the empirical study of hypotheses 2, it was discovered that an considerable favorable relationship between Relative Advantage and **(RA)** and AI Implementation (AIIM) (R-square

= 0. 994; Beta coefficient =0.161; t-value =1.854). The adoption of AI is significantly impacted by this significant sub-dimension. According to Yadegaridehkordi et al. (2018), as supply chain companies become more aware of the advantages and benefits of large-scale data and artificial intelligence (AI) technologies, a sustainable environment of utility will be developed, leading to a high rate of AI adoption.

There is a noteworthy positive correlation between the two constructs. was found by independently examining the relationship between **Managerial Support (MS)** and AI Implementation (AIIM). This finding supports Hypotheses 3 (R-square = 0.994; Beta coefficient = 0.939; t-value = 72.400). According to a Yang et al. (2015) study, upper management commitment and support have a significant connection to the adoption of technology. This relationship is especially important when it comes to developing strategies and guiding the latest emerging technologies. It is imperative that managers have assessed the infrastructure and supportive environment required for incorporating AI into the supply chain operations. By participating during the procedure and allocating managers can use organizational resources to encourage the adoption of AI. To successfully complete IS projects, top managers can also decide on the purpose, vision, policy, and direction for staff members (Intakhan, 2014). The ability of a company's top managers to use The strategic core competency of AI applications is crucial for the adoption of AI. This outcome is consistent with earlier research on the uptake and application of cutting-edge technologies Yang, Sun, Zhang, & Wang, 2015).

The empirical study of hypotheses 4 revealed a significant negative correlation between **Cost (COST)** and AI Implementation (AIIM) (R-square = 0.994; beta coefficient = -0.014; t-value = -1.462). The cost-saving element is the primary motivator, followed by increased efficiency and the acquisition of real-time data and analytics. Cost savings were identified by as one of the primary drivers because they resulted from fewer errors, quicker identification, shorter search times for materials and information, and simple data access. state that cost containment and efficiency go hand in hand. As efficiency rises, fewer resources are required, which lowers the cost and duration of carrying out Supply Chain tasks (Toorajipour et. al. 2021).

The empirical study of hypotheses 5 revealed a strong positive correlation between **Technical Capability (TC)** and AI Implementation (AIIM) (R-square = 0.994; Beta coefficient =0.024; t-value = 2.141). Technical capabilities that are necessary for the effective implementation of AI integration include the availability of skilled human resources and a strong infrastructure. When making decisions about adopting AI, decision makers can take into account and investigate the most recent technological advancements thanks to the Testing and adaptability of AI systems Numerous studies substantiate the idea that technical aptitude does indeed promote the adoption of IT (Garrison et al., 2015).

Most notably, the results (hypotheses 6) demonstrate that **Competitive Pressure (CP)** significantly affects AI Implementation (AIIM) (R square = 0.994; Beta coefficient = 0.367; T value = 15.237). For the AI industry, competitive pressure is crucial because it can encourage utilizing state-of-the-art technologies like block chain technology (BT), machine intelligence (ML), and the internet of things (IoTs) to accomplish the objective of creating a flexible and durable AI channel. (Affia et al. 2019). Supply chain industries may always imitate other businesses' strategies to demonstrate their capabilities to competitors due to competitive pressure. Various studies on IT adoption indicate that decisions about IT adoption are influenced by changes in the external market environment. They discover that a company in intense competition has a strong incentive to discover inventions that will support its efforts to maintain and expand its competitive advantages.

According to the independent study, there is a constructive correlation between the two constructs of **Government Support (GS)** and AI Implementation (AIIM) (R-square = 0.994; Beta coefficient = 0.240; t-value = 10.846). The environment created by the government is conducive to the progress and implementation applications of AI. According to Alreemy et al. (2016), the employ of AI technologies within the chain of supply now be supported by the presence of appropriate regulations and adequate financial funding. This is because companies may face pressure from government regulators to integrate new technologies into their supply chain operations.

The empirical study of hypotheses 8 revealed a substantial negative correlation between **Market Uncertainty (MU)** and AI Implementation (AIIM) (R-square = 0.994; Beta coefficient = -0.014; t-value = -1.475). Supply chain mechanism's main obstacles have been identified as market uncertainty and demand volatility. Businesses must use cutting-edge technologies to exhibit a high degree of agility due to unpredictably fluctuating demand in order to avoid the supply chain's market demand's volatility and uncertainty (Abolghasemi et al., 2020).

The findings of studies examining the connection between **Vendor Partnership (VP)** and AI Implementation (AIIM) (H9; R-square = 0.994; Beta coefficient = 0.249; t-value = 11.278) verified the presence of a significant positive relationship. According to Oliveira and Martins' (2010) research, Vendors are unique and important in the field of artificial intelligence. Businesses typically lack the knowledge and resources necessary to support innovations like artificial intelligence applications. Massive financial resources and top-notch talent are needed for autonomous AI research and development. Additionally, vendors require all relevant data from their clients. Therefore, it makes sense for businesses to deploy AI applications in collaboration with partners and vendors. The correct suppliers of AI technology can offer a productive means of collaboration and guarantee that the company's competitive advantage is strengthened rather than weakened by such cooperation.

Based on the empirical study of hypotheses 10, it was discovered that there is a constructive negative correlation between **Complexity (COMPL)** and AI Implementation (AIIM) (R-square = 0.994; Beta coefficient = -0.411; t-value = -18.425). Artificial intelligence (AI) technology is a multifaceted knowledge-based system, so before implementing it in operations and supply chain activities, an organization should train its staff and end users appropriately. Providers of AI technologies provide their clients with a range of services, from maintenance to service installation. As a result, supply chain companies that use AI services do not require a large number of specialists to update and maintain the infrastructure. Any supply chain company experiencing issues can get in touch with the AI provider's business and request that they resolve the problem (Hentschel, Leyh, and Baumhauer 2019).

There is a noteworthy positive correlation between the two constructs. was found by independently examining the relationship between **AI Implementation (AIIM**) and SCM Performance (SCMP). This finding supports Hypotheses 11 (R-square = 0.667; Beta coefficient = 0.816; t-value = 34.458). According to Saberi et al. (2019), If the supply chain companies want to maintain the organization's leverage in between its goal and vision, they should integrate artificial intelligence (AI) and digital technologies across the network of supply chains.

8. CONCLUSION

Through the use of research methodologies and data processing, the study findings show that variables influence the decision to implement AI applications in supply chain management. These factors have been modified to better fit the research topic when compared to the other proposed research model. Examining these variables is anticipated to have a positive impact and assist strategic planners in developing plans to use AI to support the operational requirements of the company both now and in the future. Research findings have aided companies in realizing the value of artificial intelligence, developing strategies and plans to swiftly transition to digital technology and streamlining workflows to improve supply chain efficiency.

Our work opens up exciting new directions for future research and makes important contributions to theory and practice. This research offers varying perspectives on the fundamental elements that elucidate the AI-specific elements that impact an organization's inclination to embrace AI. This contribution begins with defining artificial intelligence in terms of organizations and information systems. Furthermore, this study deepens our knowledge of the adoption of technology. To provide a more comprehensive framework, this research integrates well-established theories with a large body of AI research literature. The review of the literature revealed a paucity of studies on the elements that encourage businesses to use artificial intelligence.

The findings show that, despite certain limitations, when included in the framework for implementing AI can provide a deeper understanding of how to apply AI effectively at the corporate level. Thus, future studies might concentrate on other elements, like how laws and regulations impact AI adoption. Further research on these topics and building upon the results of this exploratory research is necessary to obtain a deeper understanding of the adoption of AI and its practical application.

9. FUTURE PROSPECTS

The investigation concludes that the most solid impact on the use of AI in business comes from the identification of relative points of interest in the field. In this way, efforts are needed to increase industry and user awareness of the advantages of artificial intelligence. There are several reasons to be interested in using AI to support learning. Innovative approaches like personalized learning, AI-powered chat bots, constructive criticism, and learning analytics, among others, have proven to be incredibly accommodating in increasing productivity. When compared to people, these seem to be the varied highlights of AI.

Further interviews or the gathering of second-hand data are needed to obtain more reliable information about the study, which will strengthen the case for it in subsequent studies. The study looks only at how businesses' willingness to use artificial intelligence technologies affects supply chain performance and resilience. Hence, given the complexity of the relationships between these businesses and their many partners, future research must contrast and clarify the supply chain's upstream and downstream positions in order to offer more novel and useful insights. It should also include additional supply chain domains.

10. LIMITATIONS

There are four problems with this research. Because of constraints in terms of time, money, and resources, the initial focus of this research was only the business market. The rationale behind adoption intentions and their consequences differ based on the artificial intelligence capabilities' architecture and technical framework of different countries' businesses. Consequently, disparities exist in external motivation and advocacy for the adoption of artificial intelligence technologies. The research object should be expanded to more countries and locations in the future in order to strengthen the study's conclusion's universality.

Second, we conducted an empirical test of our claims using survey data from businesses. Our focus on business operations would limit the applicability of our findings to businesses operating in other regions, though, as a large developing economy's subnational areas may have very different institutional, industrial, and economic environments. It is therefore recommended that additional research be done to see if the findings of our analysis vary based on the area in which the businesses are located.

Thirdly, compared to individual users, corporate users' questionnaire response rates are lower. During the examination, many businesses refused to divulge confidential information about their financial status, technological innovations, and use of artificial intelligence.
Lastly, we were unable to examine the connections that our causality-theoretic model predicted because we tested our hypotheses using survey cross-sectional data. We hope that future research will be able to address this shortcoming and improve the applicability of our theoretical framework by utilizing large, long-term datasets and historical data.

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