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Artificial Intelligence Application in Supply Chain Management in the Government Sector of Pakistan †

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Abstract: As the world is becoming more digital, private companies are now using cutting-edge technologies to streamline their operations and increase public trust. In countries like Pakistan, where the government is in charge of most public services, technological adoption is premature for a number of reasons. This study identified the use of artificial intelligence (AI) in five different management components, such as demand management, procurement management, logistics management, disposal management, and risk management which contribute to enhancing overall supply chain management performance in the public sector. Research found that bureaucracy is the crucial adoption barrier that existed in Pakistan's public distribution systems, with AI being the most popular technology.

Keywords: AI applications; supply chain management; government sector; performance; bureaucratic barriers

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1. Introduction

Supply chain management (SCM) has become a prominent focus in the current financial management reform initiatives in the public sector of Pakistan [1]. Supply chains are becoming more susceptible to breakdowns as a consequence of a rising number of calamities like catastrophes, pandemics, prompt operations, and worldwide distribution networks [2]. Nearly five million corporations, consisting of more than 90% of Fortune 1000 companies, possessed multiple tier-2 vendors in the region most affected in China over the early months of the outbreak, according to Ghadir et al. [3] on the influence of COVID-19 pandemic on global gross domestic product. There are no exemptions in the public sector as well. The utilization of Artificial Intelligence (AI) in SCM has garnered increasing attention. Nonetheless, the extent of scholarly research into the implementation of AI within SCM at the governmental level throughout the public sector in Pakistan has been constrained. The primary objective of this study is to ascertain the determinants that impact AI applications in SCM performance across the governmental sector of Pakistan. Further, how do bureaucratic barriers in AI implementation moderate the association between AI Applications in supply chain management in the government sector and supply chain management performance? This study encompasses various government sectors, specifically the National Food Security (NFC), Food Processing Authority (FPA), Directorate of Food (DF) for wheat, and logistics.

2. Literature Background and Hypotheses

2.1. Definition of AI

The domain of AI has undergone significant developments in recent decades, leading to a continuous evolution of its definition and application. Previous studies confirmed the use of AI in health and education [4], e-governance, private industry [5], and decision-making [6]. Presently, AI applications are primarily categorized under Big Data, Deep Learning (DL) and Artificial Neural Networks (ANN), which constitute their fundamental elements [7]. The present study adopts deep learning methodologies that employ artificial neural networks as the operational definition of artificial intelligence.

2.2. Definition of Supply Chain Management

As per the findings of Restuccia and Taska [8], the most important competencies for positions associated with supply chain management encompass budgeting, scheduling, procurement, project management, logistics, resource planning, and supply chain management. Handfield [9] stated for the business of government, a supply chain "encompasses all activities associated with the flow and transformation of materials and services from inbound upstream suppliers through to end users via downstream distribution and a service provider network". Products, services, resources, and information all move through the supply chain. The integration of different initiatives is crucial for achieving specific objectives in management, such as enhancing food supply capacity, demand management, procurement management, logistics management, disposal management, and risk management.

2.3. Supply Chain Performance

The evaluation of supply chain performance involves a retrospective analysis aimed at assessing compliance with appropriate processes and fulfilling intended goals [10]. The National Treasury of the Pakistan Government has devised a formal report blueprint that is utilized by provincial treasuries for supervising the implementation process of SCM at the respective localities. For improvements in supply chain performance, it is predicted that local governments will adopt a framework for perpetual enhancement. In accordance with the SCM policy, it is incumbent upon each government organization to customize the policy to comply with its specific requirements. The frameworks utilized for the management of supply chain operations inside the country exhibit distinctness [1]. The aforementioned framework delineated the specific responsibilities and obligations assigned to individuals tasked with implementing SCM. The SCM policy mandates the establishment of management committees. Several committees are planned to be established, namely the demand and supply committee, procurement committee, and disposal and logistics committees. Figure 1 illustrates the most significant factors contributing to SCM performance.

Figure 1. Influencing factors of SCM performance.

2.4. Applications of AI in Supply Chain Management

The prompt progressions in the arena of AI have facilitated its development in multiple domains of SCM. Previous research presents a comprehensive overview of the principal domains in which effective implementation of AI has been documented in scholarly literature [11]. The advantages of implementing AI encompass enhanced SCM performance in warehouse management [12], reduced costs, enhanced customer satisfaction through ensuring product availability, and decreased downtime through scheduled maintenance, ultimately leading to increased SCM performance [13]. Another area of current research and application pertains to the potential utilization of AI in facilitating supply chain operations during disaster management circumstances. Specifically, there is a focus on optimizing resource allocation and distribution through the implementation of feasible planning strategies [14].

2.5. Demand Management (DM)

The implementation of SCM is followed by an obligation for a need assessment (demand). The purpose is to guarantee that the products and services supplied satisfy the specifications of the determined demands. The implementation of an integrated development plan by a local government guarantees the timely, cost-effective, and appropriate delivery of resources necessary to satisfy identified needs [15]. Furthermore, both the quality and quantity of these supplies are ensured to be satisfactory in meeting indicated needs. The integration of AI in SCM has the potential to provide advanced optimization capabilities that can enhance the accuracy of demand projections and promote safer work environments.

Hypothesis 1. *AI application in DM impacts SCMP positively*.

2.6. Procurement Management (PM)

This pertains to the management and oversight of the acquisition process. The strategy for handling market dynamics is determined by each governmental entity, which also forces the total cost of acquiring assets, verifies the completeness of bid documents and evaluation guidelines, determines bids based on published standards, and guarantees the proper execution of contractual documents [16]. AI application in SCM has the potential to provide robust optimization features to enhance the accuracy and efficacy of bidding and price forecasting which contributes to SCM performance.

Hypothesis 2. *AI application in PM impacts SCMP positively*.

2.7. Logistics Management (LM)

Logistics refers to the systematic management of the procurement, transportation, and warehousing of inventory within an entity and its marketing avenues. The primary objective of this process is to optimize SCM performance by efficiently fulfilling orders while minimizing costs [17]. This argument involves the integration of a particular process within the supply chain framework, which is responsible for the implementation, regulation, and facilitation of the effective distribution of stored products and services. The use of AI in SCM has the capability to deliver efficient optimization options to boost the precision and productivity of logistics systems for strengthening SCM performance.

Hypothesis 3. *AI application in LM impacts SCMP positively*.

2.8. Disposal Management (DMA)

Disposal management refers to the process of relinquishing assets that are considered unnecessary, encompassing items that are unserviceable, superfluous, or outdated. The aforementioned process involves a thorough assessment of obsolescence planning, evaluation of material for potential recycling, determination of an appropriate disposal strategy, and execution of the physical disposal process [15]. The deployment of AI into SCM can provide the correctness and efficacy of disposal management systems, ultimately leading to improved SCM performance.

Hypothesis 4. *AI application in DMA impacts SCMP positively.*

2.9. Risk Management (RM)

The term "risk" pertains to an unexpected or accidental result of a choice or behavior. Risk management using AI refers to the implementation of a proficient framework for the detection, evaluation, and prevention of potential risks. The process entails the systematic identification of potential risks on an individual basis, followed by the allocation of said risks to the party that is most capable of effectively managing them [10]. Additionally, it involves the acknowledgment and acceptance of the associated costs of these risks, proactive measures to mitigate them, and the provision of sufficient coverage for any remaining residual risks. Furthermore, the assignment of relative risks to the involved parties is achieved through the use of explicit contractual documentation.

Hypothesis 5. *AI application in RM impacts SCMP positively.*

2.10. Moderating Role of Bureaucratic Barrier (BB) in AI Implementation in SCM

During all the phases of AI's development—from the incubation/research phase to the feedback-gathering inquiries phase to the approval of applying AI within their institutions—the approval of the top bureaucracy of the government entity performs a crucial role. The management of an AI-first SCM is more likely to support innovative ideas, encourage greater levels of internal and external experimentation, and allocate resources to AI-centric projects. These executives are always expanding their perspectives and advocating for AI in internal and external executive meetings [18]. Executives of various entities seldom have expertise in machine learning and optimization, but they should all agree that using data to make decisions is preferred rather than depending on instincts. The development of an AI initiative can be disrupted if the parties are not in agreement about how to use data and how powerful AI can be [18].

Hypothesis 6. *Bureaucratic Barrier in AI adoption in SCM effects SCMP negatively.*

Hypothesis 7. *Bureaucratic Barrier in AI adoption in SCM moderates negatively on the relationship between AI in demand management and SCMP.*

Hypothesis 8. *Bureaucratic Barrier in AI adoption in SCM moderates negatively on the relationship between AI in procurement management and SCMP.*

Hypothesis 9. *Bureaucratic Barrier in AI adoption in SCM moderates negatively on the relationship between AI in logistics management and SCMP.*

Hypothesis 10. *Bureaucratic Barrier in AI adoption in SCM moderates negatively on the relationship between AI in disposal management and SCMP.*

Hypothesis 11. *Bureaucratic Barrier in AI adoption in SCM moderates negatively on the relationship between AI in risk management and SCMP.*

3. Methodology and Results

This study employed a quantitative methodology for collecting sample data by administering paper-based survey questionnaires to the employees performing duties in the NFC, FPA, and DF departments in Pakistan. The collected data sample was analyzed using SmartPLS 4, which involved a range of confirmatory factor analysis (CFA), correlation, and structural equation modeling techniques. This method actually remains unharmed by the small sample size also. The representative sample was established by previous scholars through adherence to the suggested standard for survey question volume, as outlined [19]. Following the distribution of questionnaires to employees, a total of 546 completed questionnaire responses were collected for analysis. Measurement reliability was assessed using outer factor loading and composite reliability. Convergent validity analysis was conducted to examine the Average Variance Extracted (AVE) of the factors. The Cronbach's alpha coefficient was utilized to assess the internal consistency of the constituent elements.

4. Results

For the measurement model, items with structured factor loadings of 0.70 or higher were considered reliable [20]. Composite reliability determined component construct reliability. Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) indicate variable reliability and validity. All seven framework constructs exceeded the minimum significance threshold, indicating convergent validity.

Table 1 presents the results of a structural equation modeling study on the effects of AI applications in SCM on SCMP and the moderating effect of bureaucratic barriers on the SCM-SCMP relationship. The findings suggest that AI applications in SCM had a positive effect on SCMP, supporting H1, H2, H3, H4, and H5. To test Hypotheses 6, 7, 8, 9, 10 and 11, we developed a moderated-hypothesis testing framework that accounted for bureaucratic barriers to AI adoption for SCM's moderating effect on the relationship between AI applications in SCM and SCM performance. The negative interaction effects of bureaucratic barriers weaken the relationships between independent and dependent variables. Hence, H6–H11 were supported.

Table 1. Structural Equation Modelling Outcomes.

	Original Sample (O)	Sample Mean (M)	Standard Deviation	T Statistics (|O/STDEV|)	*p* Values	Results
Demand Management → Supply Chain Mgt Performance	0.634	0.433	0.006	5.902	0.000	Supported
Procurement Management → Supply Chain Mgt Performance	0.742	0.743	0.009	4.864	0.008	Supported
Logistics Management → Supply Chain Management Performance	0.456	0.357	0.014	3.884	0.012	Supported
Disposal Management → Supply Chain Management Performance	0.663	0.765	0.011	7.431	0.007	Supported
Risk Management → Supply Chain Management Performance	0.506	0.601	0.031	18.074	0.024	Supported
Bureaucratic Barriers → Supply Chain Mgt Performance	−0.919	−0.639	0.018	−23.142s	0.041	Supported
Demand Management × Bureaucratic Barriers → SMCP	−0.052	−0.031	0.019	−12.756	0.006	Supported
Procurement Management × Bureaucratic Barriers → SMCP	−0.592	−0.468	0.022	−18.009	0.000	Supported
Logistics Management × Bureaucratic Barriers → SMCP	−0.493	−0.392	0.027	−7.231	0.009	Supported
Disposal Management × Bureaucratic Barriers → SMCP	−0.492	0.498	0.022	−9.009	0.003	Supported
Risk Management × Bureaucratic Barriers → SMCP	−0.255	0.185	0.087	−7.532	0.000	Supported

5. Conclusions

5.1. Implications

The desire to adopt AI in the field of SCM is rapidly growing into a government priority as the government sector in Pakistan eventually recovers from a global epidemic that has decimated operations and supply chains worldwide. Additionally, plenty of research and emphasis will be focused on the significance of AI as it relates to the larger SCM domain in several decades to come. For this, it is crucial to get to know the factors affecting the adoption, application, and routinization of AI in SCM for improved performance. The authors contend that the suggested and examined conceptual framework with key elements will facilitate additional investigations and experimental studies. Moreover, this study will be highly beneficial to bureaucrats, supply chain organizers, and management experts as they develop plans for their organizations' adoption, implementation, and routinization of AI in the realm of SCM.

5.2. Concluding Remarks

The present study offers a comprehensive examination of the factors that impact the implementation of AI in SCM and their consequential effects on the performance of SCM. The impetus for this research was the observation that extant models tend to overstate the impact of bureaucratic barriers on SCM performance. To bridge these identified gaps, a more inclusive framework for SCM performance was devised and subsequently implemented across a broader spectrum of instances. The results indicate that there exist noteworthy bureaucratic barriers to the impact of moderation on the association between AI in SCM and supply chain management performance (SCMP).

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