

AN ENHANCED MODEL FOR SUPPLY CHAIN RESILIENCE IN THE EFFECTIVE USE OF ARTIFICIAL INTELLIGENCE

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Abstract

Background: The integration of Artificial Intelligent (AI) into supply chain management has emerged as an important strategy for enhancing operational efficiency and supply chain firm resilience in business organizations, while supply chain refers to the network of people, organizations, activities, information and resources involved in the creation and distribution of goods and services to customers, supply chain resilience is the ability of a firm to withstand, adapt and recover from disruptions while maintaining its core functionality and performance objectives. This study proposed an enhanced model of supply chain management (SCM) by integrating two important factors namely: leadership and employee proficiency, and data quality management, into an already existing research model. **Aim:** The enhanced model aims to provide a more comprehensive understanding of the dynamics of SCM. **Method:** Data were collected from 115 information technology (IT) and business specialist. Online questionnaires were sent directly to respondents' personal business e-mail addresses with the purpose of the research stated. Data collected were analyzed using IBM SPSS Statistics 20. **Result:** Result indicates that the addition of these factors significantly enhanced the model's explanatory power, with firm resilience (FR) emerging as a statistically significant contributor with value 0.487, as $p(0.000) < (0.05)$ which proves that there are substantial contributions from FR to AI use (AIU). Also, the unstandardized coefficients for variables leadership and Employee proficiency, (LEP) and Data Quality management (DQ) are; 0.27 and 0.149 respectively. Which also shows that a unit increase in any of these independent variables holding others constant will bring about an increase in the dependent variable AIU by 0.27 for LEP and 0.149 for DQ with their p values (0.710 and 0.206) > 0.05 which shows that each of these independent variables even though positive were not statistically significant. The findings suggest that leadership, employee proficiency, and data quality management play critical roles in fostering resilient supply chains, ultimately leading to improved performance and competitiveness. This research contributes to the ongoing efforts to refine SCM theory and practice, providing valuable insights for scholars and practitioners alike.

Keywords: Artificial intelligence, Supply Chain Management, Leadership, Supply Chain Resilience and Employee Proficiency.

1. Introduction

In today's dynamic business landscape, where disruptions are the norm rather than the exception, the resilience of supply chains has emerged as a critical determinant of organizational success. With the advent of Artificial Intelligent (AI) technologies, businesses have been presented with unprecedented opportunities to fortify their supply chain resilience. According to Grover et al. (2020) and Sullivan and Wamba (2022), AI is the ability of a system to acquire learnings by analyzing the external environment's data and using

acquired learnings to adjust or make new plans against environmental changes. Using machine learning algorithm to learn patterns from text data, virtual agents and robotic automation to support business process (Sturm et al., 2021). Organizations are increasingly using AI that opens up new possibilities for the relationship between human and machines to perform tasks on digital platforms (Rai, et al., 2019). While supply chain refers to the network of people, organizations, activities, information and resources involved in the creation and distribution of goods and services to customers. supply chain resilience is the ability of a firm to withstand, adapt and recover from disruptions while maintaining its core functionality and performance objectives. Resilient supply chain can effectively withstand various challenges such as natural disasters, geopolitical events and market fluctuations interrupting the flow of goods and services offered by organizations. Consequently, disruptions in the supply chain can have negative consequences on firm performance, lowering both stock returns and firms' competitive positioning in the markets (Ivanov & Dolgui, 2020). Sullivan and Wamba (2022), states how the integration and use of AI affects firm performance, in various areas such as customer insights, marketing, supply chains, operations. They note how the use of AI improves firm's operational performance and enables firms to continually develop a series of temporary advantages in supply chain. For example, businesses are increasingly making use of AI systems to overcome information processing constraints inherent to supply chain, resulting in innovative paths of designing new products, solving supply chain issues and satisfying customers, and eventually, improving firm performance (Belhadi et al., 2021). Mikalef and Gupta (2021), AI capability as a high-order construct including several dimensions, such as tangible resources, human skills, and intangible resources. Result from their study indicates a positive and significant relationship between AI and organizational performance. Similarly, Li et al. (2022) found a positive and significant relationship between AI and organizational performance, mediated by knowledge management processes. Dubey et al. (2020) found that AI usage enables analytics capabilities that has a positive and significant impact on firm operational performance that is, the more, a firm is provided with capabilities to use AI to create dynamic capabilities that enable it to coordinate its resources, improve and renew technological knowledge, and modify its resource base, the higher its performance will be. However, while extant literature has recognized the important role of firm resilience as a mediator between AI utilization and firm performance (Sullivan & Wamba, 2022), Factors such as leadership and employee skills, data quality and infrastructure also play indispensable roles in shaping firm performance within AI-enabled supply chains. According to Moslehpour et al. (2019), resilience alone may not suffice in determining organizational success; in order to directly and indirectly enhance an organization's performance, a firm must increase the efficiency of its organizational leadership. Sheshadri et al. (2021), empirically tests how data and tool acquisition are two important components for business analytic capabilities that can improve the business value of the organization thereby leading to an improved organizational performance. Building on the dynamic capability theory, the study endeavors to address this relationship by proposing an enhanced research model that surpasses the conventional focus on firm resilience as a standalone determinant of firm performance. By integrating other key factors such as leadership effectiveness and employee skill development initiatives and data quality management practices. Through empirical validation, the study aims to provide an understanding of the intricate interplay between AI adoption, supply chain resilience, and other mediating factors that contributes to the organizational performance, thereby offering actionable insights for practitioners and contributing to the advancement of knowledge in the field of supply chain management.

2. Related Works

Dynamic capabilities enable organizations to integrate, build, and reconfigure their resources and competencies Magnano et al. (2024). In order to understand the essence of dynamic capabilities, previous research suggests the difference between ordinary and dynamic capabilities ordinary capabilities can best be thought of as "achieving technical efficiency and "doing things right" in the core business functions of operations, administration, and governance", dynamic capabilities "help enable an enterprise to profitably build and renew resources and assets that lie both within and beyond its boundaries, reconfiguring them as needed to innovate and respond to (or bring about) changes in the market and in the business environment

more generally". Three fundamental processes that make up basic dynamic capabilities: (1) learning; (2) coordinating/integration; and (3) strategic competitive reaction processes. The essential traits of dynamic capabilities are reflected in these AI skills. The ability of a company to use and evaluate the worth of its current resources and integrate them to create new capabilities is referred to as coordination and integration. Coordinating and integrating entails synchronizing various activities and efficiently coordinating a range of tasks and resources. An organization's applications of AI across their supply chain enable greater dynamic information processing capability that can be used to gather and interpret data, enabling organizations to easily allocate resources and tasks (Benbya et al., 2020).

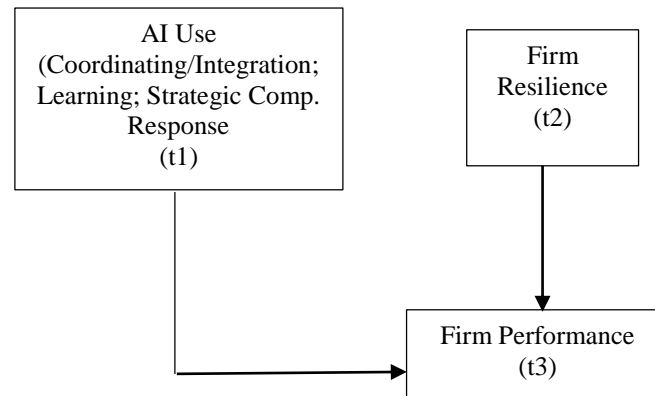


Figure 2.1: Research model (Sullivan & Wamba 2022).

Grounded on the dynamic capability theory of the firm, Sullivan and Wamba (2022). AI use as a dynamic information processing capability consisting of three dimensions: coordinating/integration, learning, and strategic competitive response capability as an antecedent of firm resilience to supply chain disruptions, and firm resilience as a mediation factor that links AI use and firm performance. By analyzing the data gathered using a two-stage survey from 107 companies in Europe, the study result indicates AI use has a direct impact on firm resilience, and firm resilience fully mediates the relationship between AI use and firm performance.

As shown in Figure 2.1, Scholars defined AI as the process of using computers to mimic the learning, reasoning, planning, and other cognitive functions of humans in order to solve complex issues that were previously only able to be solved by human experts (Lei and Wang, 2020). Benbya et al. (2020), notes how an organization's applications of AI across their supply chain enable greater dynamic information processing capability that can be used to gather and interpret data, enabling organizations to easily allocate resources and tasks, Sturm, et al. (2021), established knowledge creation routine (learning) and while Lawless et al. (2019) reduce uncertainty by stimulating insights Similarly, Wamba et al (2020), carried out a study to analyze how AI can influence firm performance. The methodology employed was based on a review of 500 case study from IBM, AWS, Cloudera, Nvidia, Conversica, Universal robot website, by making an archival data analysis based on two phases namely the refinement and development, and the assessment phase. Findings reveal how AI can improve performance and benefits both organization finance, marketing, administration and process levels. Haefner (2021), outlined the organizational structure of innovation management and how artificial intelligence shapes businesses. The firm's behavioral theory and concepts from the Carnegie School are both incorporated into the process. The study's findings illustrated how much AI can replace human labor and clarified key factors to take into account when transforming into a digital innovation organization. The study finds that AI can provide solutions for efficient resource management that surpass the limitations of humans. Berente et al. (2020), also notes how AI provide businesses with novel opportunities for designing intelligent products, devising novel service offerings, and

inventing new business models. They argue that the information processing power of AI can facilitate this coordination capability by augmenting human skills to organize and coordinate organizational core activities. This coordination capability could “lead organizations toward dynamic organizing and competitive advantage upon the introduction of intelligent technologies”. Some authors even argue that AI can “enable organizations to divide and allocate tasks as well as to integrate efforts in novel ways” [27, p. 67]. AI enables the integration of business systems with business or manufacturing operations that reduces process variation and improves global optimization. Sullivan and Wamba (2022) defined Learning capability as the firm’s ability to explore and learn new ways while at the same time exploit what have already learned. Processing information using AI can support organizational learning and enable firms to form and execute business strategies effectively. According to Ransbotham et al. (2020), Organizations that learn with AI can refine business processes quickly as circumstances changes. As people in an organization continue to learn, their perception of a problem may change. When this happens, AI systems can be realigned with humans’ current problem understanding to facilitate learning. Therefore, organizational learning supported by AI’s information processing capability is an important process, which through an interaction with human users, leads to increased firm performance (Sullivan & Wamba 2022) Salovaara (2019), in his study on high reliability in digital organizing: Mindlessness discussed how AI is increasingly capable of outperforming humans in terms of quickly responding to changing and complex situations. AI can generate insights that firms can use in a decision processes]. For example, machine learning applications are being used to detect patterns in vast volumes of data and interpret their meaning. While existing studies have established the role of AI in improving supply chain resilience and firm performance, limited research has explored the integration of leadership and employee proficiency (LEP) and data quality management (DQ) as mediating factors. Previous models focused primarily on firm resilience as the sole mediator, overlooking how these additional factors contribute to AI utilization and overall supply chain efficiency. This study addresses this gap by empirically testing the impact of LEP and DQ, thus broadening the scope of AI-driven supply chain resilience research.

3. Methodology

This research employed a quantitative approach, and utilized a survey method to gather data on the relationship between mediating factors such as firm resilience, data quality management, leadership and employee proficiency in the effective use of AI. The study developed an enhanced model that identified key factors influencing AI use and Firm performance and how AI can be integrated to bolster these factors, IBM SPSS Version 20 software was used to run the analysis of the collected data.

3.1. Source of Data

The study adopts the methodology of (Sullivan & Wamba, 2022). The Organization involved in the supply chain comprises the study's unit of analysis. The focal point of the supply chain is the organization, which is connected to both customers and suppliers. IT firms and business executives are the main source of the study population. They are regarded as a data source.

3.2. Data Collection Method

After establishing the population, the data collection method was constructed. Since the survey attempts to measure AI use, Firm resilience, Leadership and Employee proficiency, and Firm performance. IT and business specialist will be used because they are considered as the most appropriate respondents to provide sufficient data for the research purposes. After reaching correct respondents' e-mails, online questionnaires were sent directly to respondents' personal business e-mail addresses. In e-mails, the purpose of the research will be explained and online entry will request to attach the link of the questionnaire. The survey will be conducted over a 1-month period. The design and content of the Questionnaire The intention of the questionnaire is to measure AI use, Firm resilience, Leadership and Employee proficiency, and Firm performance in a supply chain. This study used the Likert scale, which is accepted as the most frequently

used variation of the summated rating scale. In Likert scales, responses over a number of items tapping a particular concept or variable are then summated for every respondent (Sekaran, 2003). Five measurement items will be used with responses ranging from (1- Not at all, 2- slightly agree, 3- Moderately, 4- Very much, 5- Completely).

The questionnaire will be divided into several sections to capture relevant information:

1. Demographic Information: This section will collect basic information about the respondents, including: Age, Job title, Industry sector
2. Key Factor: This section will include questions to measure the key factors contributing to AI use, firm resilience, Leadership and employee proficiency, Data Quality management and Firm Performance adapted from previous research.

3.3. Model Formulation

This study employed quantitative statistical analysis. Regression analysis is a method used to examine the relationship between one dependent variable and one or more independent variables, called predictors or explanatory variables. It helps in determining how the dependent variable changes when any one of the independent variables is varied, while other independent variables remain constant (Shrestha, 2020). In this study, multiple regression analysis method was used to show relationship between the dependent variable Y (AI use) and independent variables (Firm Resilience, Firm performance, leadership and employee proficiency, data quality management), (X₁, X₂, X₃... X_n) respectively, hence this model takes the form of:

$$Y = f(X_1, X_2, X_3, \dots, X_n) \dots\dots\dots 1$$

And thus,

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n + \epsilon \dots\dots\dots 2$$

Where Y = Dependent Variable (AI Use)
 β_0 = Intercept of the function (Constant)
 $\beta_1, \beta_2, \beta_3, \dots, \beta_n$ = unstandardized Coefficient for each predictor.
 X_1, X_2, \dots, X_n = Independent Variables
 ϵ = error term

The unstandardized coefficients (β), indicates the amount of change in the dependent variable (AIU) for a one-unit change in the predictor variable, holding other variables constant. The disturbance or error term (ϵ) represents other determinant that cause a change in the dependent variable (Y) other than the independent variables (X_j) in a model (Njoh, 2021). Therefore, the error term represents determinants of AIU other than independent variables (X_j).

3.4. Model Evaluation

The regression results are evaluated to test the significance of the variables. This is very important in order to know the statistical consistency of the parameters estimates (Njoh, 2021). The evaluation consists of deciding whether the estimated parameters are both theoretically meaningful and statistically satisfactory, through F- statistic Test (ANOVA).

3.4.1. F- Statistic Test (ANOVA)

The F- test is also called the analysis of variance (ANOVA). The F-test is used to find out whether the explanatory variables (X_i) actually have any significant influence on the dependent variable (Y) (Stoker et al., 2020). This tests the overall reliability of the method at 5% level of significance. It is the test of stability

of the regression coefficient. That is, whether the parameter estimates will remain stable overtime. Both the analysis of variance and regression analysis have as their objective, the determination of the various factors which cause variation of the dependent variable, and this similarity has led to the combination of the two methods in most scientific fields (Stoker et al., 2020).

3.4.2. Test of Goodness of Fit (R^2)

This test is important because, the closer the observations to the line, the better the goodness of fit. i.e. The better the explanation of the variations in the dependent variable (Y) by the changes in the independent variables (X_i). The coefficient of determination gives the overall strength of association between the dependent variable(Y) and the independent variables (X_i). The value of R^2 is between 0 and 1, and the higher the R^2 the better the ‘goodness of fit’ of the regression plane to sample observation, and the closer to zero (0), the worse the fit This means that higher value of R^2 , but less than 1 implies that, the regression equation has a very high explanatory power and the regression line is a ‘good fit’ (Shrestha, 2020).

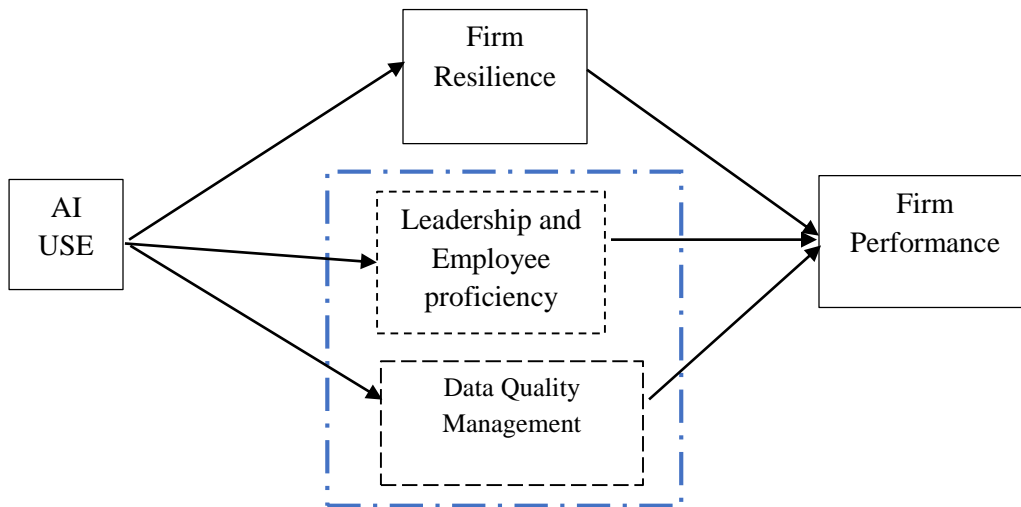


Figure 3.1. Proposed enhanced model for supply chain resilience in the use of AI

In enhancing the research model, mediating factors relevant for firm performance were identified based on dynamic capability theory and scholarly literatures. The factors identified include leadership and employee skill, Data quality management. The effective use of AI, resilience, and performance of a company are contingent upon the management of data quality, leadership, and personnel competencies. Informed decision-making by AI systems is ensured by good data quality management, and resources and direction are provided by strong leadership. Additionally crucial are employee abilities in AI creation and maintenance. These elements work together: leadership, staff competencies, data quality management, and AI adoption all support efficient AI use and overall business success. AI adoption also drives company performance and resilience. These elements work together to generate a positive feedback loop that eventually results in the success of the organization.

4. Result

In enhancing the research model, mediating factors relevant for firm performance were identified based on dynamic capability theory and scholarly literatures. The factors identified include leadership and employee skill and Data Quality Management.

4.1. Validation of an enhanced research model of supply chain resilience

In order to achieve the third research objectives which is to validate the model the study applied the use of multiple regression analysis, employed using IBM SPSS Statistics version 20.

To validate the enhanced AI model, the study conducted a multiple regression analysis incorporating the newly added factors DQM and LEP into an existing model that originally included AI Use, Firm Performance, and Firm Resilience. This analysis aimed to assess the significance of the model as a whole and determine the contributions of individual factors.

4.1.1 Determining how well the model fits.

From the model summary in Table 4.2 the values of R, R² and adjusted R² are given used to determine how well the model fits

Table 4.1: Descriptive Statistics

	Mean	Std. Deviation	N
AIU	10.2870	2.80277	115
FR	6.3304	1.91358	115
LEP	16.7565	3.53576	115
DQ	10.7130	2.16335	115

Table 4.2: Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.383 ^a	.147	.124	2.62366	1.946

a. Predictors: (Constant), DQ, LEP, FR

b. Dependent Variable: AIU

From the model summary, the value of R = 0.383 represents the Pearson correlation. This value is positive and indicates positive linear relationship between the dependent variable, AIU and the independent variable, DQ, LEP, and FR. The value of Durbin Watson was 1.946 which is greater than 1 and less than 3. This shows that there is an independence of observation (no auto correlation) and therefore it is statistically significant. And the independent variables used are truly independent. The R² value was 0.147 which showed that 14.7%, variations in AIU is explained by DQ, LEP and FR and the remaining 85.3% of the variation in AIU is accounted for by other factors not captured in this model.

4.1.2 Model Significance through ANOVA Test

Table 4.3: ANOVA^a

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	131.452	3	43.817	6.366	.001 ^b
	Residual	764.078	111	6.884		
	Total	895.530	114			

a. Dependent Variable: AIU

b. Predictors: (Constant), DQ, LEP, FR

4.1.3 Statistical Significance of the Model

The F- ratio in the ANOVA table 4.3 shows that the independent variables statistically significantly predict the dependent variable, $F(3,111) = 6.366, p(0.001) < 0.05$. That is, the regression model is a good fit of the data. It further explains that the variation that occurs in AIU is due to the use or introduction of the independent variables DQ, LEP, AND FR. In other words, there is a significant relationship between AIU and DQ, LEP, FR. Also, there is an improvement in the prediction of the variables. This is because the F ratio is greater than 1

The ANOVA result ($p\text{-value} < 0.05$), confirms that the combination of the five factors contributes meaningfully to explaining variations in the dependent variable. This result validates the inclusion of DQ and LEP as relevant additions to the model, enhancing its overall explanatory power.

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig	Collinearity Statistics	
	B	Std Error	Beta			Tolerance	VIF
(Constant)	5.157	1.610		3.203	.002		
FR	.487	.135	.332	3.608	.000	.905	1.105
LEP	.027	.073	.034	.372	.710	.906	1.104
DQ	.149	.117	.115	1.273	.206	.946	1.057

- a. Dependent Variable: AIU
- b. Predictors: (Constant), DQ, LEP, FR

The constant 5.157, is the predicted value for the dependent variable shown in table 4.4, when all of the independent variables are held constant or assumed to be 0. This means that we will expect an average increase of 5.157 in AIU. The unstandardized coefficient indicated how much the dependent variable (AIU) varies with the independent variables when all other independent variables are held constant. The regression coefficient provides the expected change in the dependent variable (AIU) for a unit increase in the independent variable referring to the coefficients (table3) above the unstandardized coefficients for FR is 0.487. This means that for every unit increase in FR there is 0.487 increase in AIU. Which is statistically significant as $p(0.000) < (0.05)$ which proves that there are substantial contributions from FR to AIU which is in line with Sullivan and Wamba (2022) work. Also, the unstandardized coefficients for variables LEP AND DQ are; 0.27 and 0.149 respectively. Which also shows that a unit increase in any of these independent variables holding others constant will bring about an increase in the dependent variable AIU by 0.27 for LEP and 0.149 for DQ with their p values (0.710 and 0.206) > 0.05 which shows that each of these independent variables even though positive is not statistically significant.

Multicollinearity problem does not exist in the model as the VIF for all variables < 10 and Tolerance is > 0.1).

Based on the result obtained from the software (SPSS version 20), the regression equation ($Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_3 X_3 + \epsilon$) can thus be estimated as;

$$AIU = \beta_0 + \beta_1 (FR) + \beta_2 (LEP) + \beta_3 (DQ) \dots \dots \dots 3$$

Where,

$$\beta_0 = 5.157(\text{Constant})$$

$\beta_1 = 0.487$ (Coefficient of FR)
 $\beta_2 = 0.027$ (Coefficient of LEP)
 $\beta_3 = 0.149$ (Coefficient of DQ)
 Thus, the specific equation becomes:

$$AIU = 5.157 + 0.027 (FR) + 0.149(DQ)$$

This implies, 5.157 is the predicted AIU when FR, LEP, and DQ are all Zero.
 For each unit increase in FR, AIU increases by 0.487, holding other variables constant.
 For each unit increase in LEP, AIU increases by 0.027, holding other variables constant and for each unit increase in DQ, AIU increases by 0.149, holding other variables constant.
 In other to determine the value of the dependent variable (AIU), from Table 4.1, the mean value for the predators is: FR = 6.3304, LEP = 16.7565 and DQ = 10.7130,
 Substituting it in equation 2

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n + \epsilon \dots \dots \dots 4$$

$$AIU = 5.157 + 0.487(6.3304) + 0.027(16.7565) + 0.149(10.7130)$$

$$AIU = 10.2902$$

The Value of AIU (10.2902), indicates the extent to which AI is utilized by the independent variables that is, how well AI adoption is supported by the current level of DQ, LEP, and Firm resilience that contributes to firm performance.

4.2. Discussion of Key Findings

The results of the analysis have several important implications for both theoretical understanding and practical applications

- i. Strategic Importance of Firm Resilience
 The significance of Firm Resilience in the model highlights its crucial role in leveraging AI technologies effectively. Firms that prioritize resilience through adaptability, resourcefulness, and risk management are better positioned to integrate AI into their operations. This underscores the need for organizations to invest in strategies that strengthen resilience, such as contingency planning and fostering a culture of innovation.
- ii. Role of Data Quality Management and Leadership Proficiency
 Although Data Quality Management (DQ) and Leadership and Employee Proficiency (LEP) were not statistically significant individually, their inclusion in the model enhances its overall explanatory power. This suggests: Data Quality Management: High-quality, well-managed data remains foundational for AI systems to function effectively. Firms must adopt robust data governance frameworks to ensure accuracy, consistency, and reliability of data.
- iii. Leadership and Employee Proficiency
 Skilled leadership and a well-trained workforce are essential for maximizing AI's potential. Organizations should prioritize leadership development programs and continuous upskilling initiatives for employees to align human expertise with technological advancements.
 The model's overall significance (from the ANOVA results) suggests that successful AI implementation requires a combination of technological, organizational, and human factors. This

implies that firms should adopt a holistic approach by simultaneously addressing AI use, firm performance, firm resilience, data quality, and employee proficiency to achieve sustainable success.

4.3. Result Implication

i. Practical Recommendations for Decision-Makers

Invest in Resilience: Firms should enhance resilience to improve adaptability and maintain performance in dynamic environments. This can involve diversification of resources and the creation of robust support systems.

i. Focus on Data Quality:

Ensuring high-quality data is critical for AI models to deliver reliable and actionable insights. Investments in data management systems and tools are imperative.

ii. Enhance Leadership and Workforce Skills:

Leadership and employee proficiency should not be overlooked. Targeted training programs and leadership coaching can empower organizations to harness AI effectively.

5.0. Conclusion

In conclusion, the study investigated the integration of relevant mediating factors in an enhanced research model in the business domain. The study presented the total of five factors by integrating leadership and employee proficiency (LEP) and data quality management (DQ) into existing SCM frameworks. An empirical validation through multiple regression analysis was conducted, demonstrating the significance of firm resilience in AI adoption, and provided actionable insights into how organizations can improve AI implementation within supply chain. Result indicates that firm resilience is statistically significant as $p(0.000) < (0.05)$ which proves that there are substantial contributions from Firm resilience to AI Use. Also, Leadership and employee skills and data quality management even though positive are not statistically significant. However, organizations seeking to integrate AI are presented with Data Quality Issues: Inconsistent and poor-quality data limited the effectiveness of AI-driven insights. Leadership Gaps: Resistance to AI adoption due to insufficient leadership engagement. Employee Skill Deficiencies: Lack of expertise in AI-related technologies slowed integration and adoption. The model highlights the interplay between AI use, firm resilience, data quality management, and leadership and employee proficiency. The significant relationships between these factors suggest that organizations should prioritize:

- AI adoption to enhance firm resilience and performance
- Data quality management to ensure accurate and reliable AI decision-making
- Leadership that champions AI adoption and provides vision and resources
- Employee proficiency in AI development and maintenance

These findings emphasize the importance of AI use to better firm performance using the mediating factors of the enhanced model.

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