Majors: SCM

Major/No. (S 7)

“Evaluating the impact of Artificial Intelligence on Supply Chain Forecasting Accuracy: The Mediating Role of Data Quality and Data Dependency.”

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BAHRIA UNIVERSITY ISLAMABAD

FALL - 2025

FINAL THESIS APPROVAL SHEET

Open Defense Examination

Open Defense Date: 13-01-2026

Topic of Research:
"Evaluating the impact of Artificial Intelligence on Supply Chain Forecasting Accuracy: The Mediating Role of Data Quality and Data Dependency."

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Abstract

This study investigates the impact of Artificial Intelligence (AI) on supply chain forecasting accuracy, with a particular focus on the mediating roles of data dependency and data quality. Rooted in the Conservation of Resources (COR) theory, the research posits that while AI holds great potential for improving forecasting performance, its efficacy is contingent upon the quality and availability of supporting data. Using a positivist, deductive, and quantitative methodology, data was collected from 384 supply chain professionals across Pakistan's retail and manufacturing sectors through a structured questionnaire. Structural Equation Modeling (SEM) was applied to test the proposed model. The results confirm that AI positively affects forecasting accuracy both directly and indirectly via the sequential mediation of data dependency and data quality. These findings provide both theoretical contributions by extending COR theory into the domain of digital supply chains and practical insights for organizations aiming to maximize AI effectiveness through robust data governance. The study highlights the importance of aligning technological investments with data infrastructure to achieve superior forecasting outcomes in emerging market contexts.

Key words: Artificial Intelligence (AI), Supply Chain Forecasting, Forecasting Accuracy, Data Quality.

Acknowledgements

I would like to express my sincere gratitude to all individuals and organizations that supported this research. My heartfelt thanks go to my academic supervisors for their continuous guidance, constructive feedback, and encouragement throughout the study. I'm also grateful to the supply chain professionals from Pakistan's retail and manufacturing industries who kindly gave their time and shared their knowledge, which made this research possible. I would like to specially thank my friends and colleagues for their useful suggestions during the data collection and analysis stages.

A special thank you goes to my friend, whose constant support, timely advice, and unwavering belief in my abilities have meant more to me than words can express. Your encouragement has been a true source of comfort and inspiration.

Completing this thesis would not have been possible without the collective support of all these incredible people. I am sincerely grateful to each one of you.

Finally, I acknowledge the support of my family for their patience, motivation, and unwavering belief in my work

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Introduction

1.1 Background

In Pakistan, the manufacturing and retail sectors are among the most important contributors to economic growth, employment generation, and national development. These sectors support a wide range of economic activities, including production, distribution, exports, and consumer markets, and collectively employ millions of people across the country (Pakistan Bureau of Statistics, 2023). Manufacturing firms play a key role in value creation and industrial output, while the retail sector acts as a direct link between producers and end consumers. Together, they form complex supply chain networks that require effective coordination, planning, and forecasting to operate efficiently.

Despite their importance, supply chains in Pakistan's retail and manufacturing sectors continue to face serious operational challenges. One of the most persistent and damaging problems is inaccurate demand forecasting, which affects inventory management, production planning, and service delivery. Poor forecasting can cause a business to have too much or too little stock, which leads to money losses, higher costs to run the business, and unhappy customers (Sharma & Hussain, 2021). Overstocking increases warehousing and holding costs, while stockouts lead to missed sales opportunities and damage to brand reputation. These issues are particularly severe in the retail sector, where product availability and timely replenishment are critical for maintaining customer loyalty.

Traditionally, many organizations in Pakistan rely on basic forecasting techniques based on historical sales data, spreadsheets, and managerial judgment. While these methods were useful in stable market conditions, they are increasingly ineffective in today's fast-changing and uncertain business environment. Factors such as changing consumer preferences, seasonal demand variations, promotional activities, and economic fluctuations make demand patterns more difficult to predict using traditional approaches (Mentzer & Moon, 2004). Additionally, old forecasting methods can't handle big sets of data or adjust quickly to changes happening in real time, making the forecasts late and not very accurate (Yuan & Zhen, 2020).

In recent years, Artificial Intelligence (AI) has become a strong tool for dealing with these forecasting problems in supply chain management. AI technologies, including machine learning and predictive analytics, enable organizations to analyze large volumes of data from multiple sources and identify complex patterns that are difficult for humans to detect (Choi et al., 2018). In supply chain forecasting, AI systems can integrate historical data with real-time information such as sales trends, customer behavior, and market signals to generate more accurate and timely predictions. Studies suggest that AI-based forecasting can significantly improve inventory planning, reduce costs, and enhance overall supply chain performance (Wamba et al., 2020).

However, using AI effectively in supply chain forecasting does not always work out. AI systems are highly data-dependent, meaning their performance is directly influenced by the availability, accuracy, and consistency of data inputs. When organizations adopt AI, their reliance on continuous and real-time data increases substantially (Gunasekaran et al., 2017). In many Pakistani firms, data is often fragmented across departments, poorly structured, or manually maintained, which limits the effectiveness of AI tools. As a result, AI systems may produce unreliable forecasts, leading to poor decision-making rather than improved performance.

Data quality is closely connected to how much data depends on other data. Data quality means how correct, full, up-to-date, and useful the data is for an organization’s systems (Wang & Strong, 1996). Good data helps AI systems learn better and make accurate predictions, but bad data can cause mistakes and unfair results in predictions. In Pakistan’s retail and manufacturing supply chains, problems like missing information, old records, and unclear ways of reporting are still common. Without strong data governance mechanisms, organizations struggle to fully benefit from AI-driven forecasting solutions.

The Conservation of Resources (COR) theory provides a useful theoretical framework to explain these challenges (Hobfoll, 1989). According to the COR theory, organizations try to get, keep, and use important resources to reach their goals. In this study, AI is seen as a key technological resource that helps with strategy. However, its effectiveness depends on the availability of supporting resources, particularly data dependency and data quality. When organizations increase their reliance on AI without ensuring adequate data quality, they risk resource loss rather than performance gains. According to the COR theory, organizations aim to obtain, retain, and use valuable resources to achieve their goals. In this study, AI is considered a major technological resource that supports strategic efforts.

As retail activities, especially online shopping, grow faster and manufacturing supply chains become more complicated in Pakistan, getting accurate predictions has become very important for businesses. Organizations are under pressure to respond quickly to market changes, reduce uncertainty, and improve operational efficiency. Understanding how Artificial Intelligence influences forecasting accuracy and the role that data dependency and data quality play in this relationship is therefore essential. This study focuses on Pakistan's retail and manufacturing supply chain sector to provide both theoretical insights and practical guidance for organizations seeking to improve forecasting performance through AI adoption.

1.2 Contextual Analysis:

Pakistan's manufacturing and retail sectors are vital contributors to the country's economy. According to the Pakistan Bureau of Statistics (2023), manufacturing contributes approximately 12% to the national GDP, while the retail sector serves millions of consumers nationwide and supports thousands of SMEs. The manufacturing sector encompasses textiles, food processing, electronics, and automotive industries, all of which rely heavily on efficient supply chain operations to maintain competitiveness in both local and international markets (Sharma & Hussain, 2021).

The retail sector in Pakistan is undergoing a significant transformation with the growth of e-commerce platforms, increased consumer demand for faster delivery, and rising expectations for product availability (Yuan & Zhen, 2020). Despite the potential for growth, both manufacturing and retail face challenges in forecasting demand accurately. Traditional forecasting methods usually rely on past sales numbers and manual changes, which can be slow to keep up with changes in the market, seasonal trends, and unexpected shifts in how customers behave. These challenges frequently result in overstocking, stockouts, high inventory holding costs, and reduced customer satisfaction (Wamba et al., 2020).

Using AI in these areas can help tackle these challenges. AI systems can analyze large datasets, detect patterns, and generate predictive insights in near real-time, potentially improving forecasting accuracy, optimizing inventory management, and reducing operational inefficiencies (Gunasekaran et al., 2017). However, how well AI works really depends on the quality of the data it uses and how well the organization can handle ongoing data flows. Inadequate data management can limit AI's potential benefits and lead to suboptimal decision making.

Thus, studying AI's impact on supply chain forecasting within Pakistan's manufacturing and retail context is both timely and relevant. It provides insights into practical implementation challenges and contributes to a theoretical understanding of how technological resources interact with organizational data practices to improve operational outcomes.

1.3 Research Gaps:

Even though there is a lot of research on using Artificial Intelligence (AI) in supply chain management, there is still not enough understanding of how AI improves the accuracy of predictions, especially in new and developing markets. Most prior studies have primarily focused on the technical capabilities of AI such as predictive modeling, automation, and data analytics without sufficiently examining the operational and resource-based factors that influence its effectiveness (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2020; Sharma & Hussain, 2021). The behavioral, organizational, and data-related conditions that enable AI to produce accurate forecasts remain underexplored (Gunasekaran, Yusuf, Adeleye, & Papadopoulos, 2017).

Conceptually, AI adoption (independent variable, IV) increases reliance on structured, real-time data inputs, creating data dependency (mediator 1, M1). However, if these data inputs are incomplete, inconsistent, or inaccurate (mediator 2, M2), the effectiveness of AI in improving forecasting accuracy (dependent variable, DV) may be significantly reduced (Hobfoll, 1989). Although several studies have examined the binary relationships such as AI and forecasting accuracy, or data quality and accuracy there is a notable lack of research integrating AI, data dependency, data quality, and forecasting accuracy into a sequential mediation framework, particularly within Pakistan's retail and manufacturing sectors (Wamba et al., 2020).

Furthermore, most AI-focused supply chain studies have been conducted in technologically advanced countries, where infrastructure, digital literacy, and organizational readiness differ significantly from emerging markets. In Pakistan, supply chains face unique challenges, including limited digitization, fragmented logistics, and variable data governance practices, which may influence the relationships among AI, data management, and forecasting performance (Sharma &

Hussain, 2021). By investigating these dynamics in the context of Pakistan's manufacturing and retail sectors, this study addresses a critical knowledge gap and contributes to understanding how AI can be effectively leveraged in emerging market supply chains (Gunasekaran et al., 2017).

1.4 Problem statement:

Despite the growing adoption of Artificial Intelligence (AI) in supply chain management, there remains limited understanding of how AI affects forecasting accuracy through operational mechanisms such as data dependency and data quality (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2020). Current research mostly focuses on the technical abilities of AI, but it doesn't look at how AI uses resources and changes behavior to lead to better performance (Gunasekaran, Yusuf, Adeleye, & Papadopoulos, 2017).

In emerging economies like Pakistan, the challenge is even more pronounced. Retail and manufacturing firms often face infrastructural limitations, inconsistent data practices, and varying levels of technological adoption, which may hinder AI's potential impact on forecasting accuracy (Sharma & Hussain, 2021). Therefore, there is a critical need to explore how AI adoption increases reliance on structured data (data dependency), the role of data quality, and their sequential effect on forecasting accuracy. Applying the Conservation of Resources (COR) theory provides a theoretical lens to understand AI as a valuable organizational resource whose effectiveness depends on supporting resources such as high-quality data (Hobfoll, 1989).

This study addresses these gaps by investigating these dynamics in Pakistan's retail and manufacturing supply chain sectors, offering both theoretical and practical insights into improving forecasting performance through AI adoption.

1.5 Research Objectives

To check if Artificial Intelligence (AI) affects how well supply chain experts in Pakistan's manufacturing and retail sectors can predict future demand. In today's quickly changing supply chain world, being able to predict accurately is very important for running businesses smoothly and keeping customers happy. This goal is about finding out how using AI directly changes the accuracy of these predictions. By looking at how AI tools help improve forecast accuracy, this study shows how AI can be a helpful technology in making better business decisions in Pakistan's retail and manufacturing industries.

To check if data dependency affects how AI influences forecasting accuracy. Effective AI systems rely heavily on continuous, structured, and timely data inputs. This objective explores how reliance on data affects the effectiveness of AI in forecasting. Understanding this mediation can reveal whether the availability and flow of data act as a bridge between AI adoption and forecasting outcomes, ensuring that AI tools deliver practical and actionable insights.

To check if the quality of data affects how well AI helps in making accurate forecasts, it's important to understand that good data is essential for any AI system that is used to predict future outcomes. This objective examines the extent to which data accuracy, completeness, and relevance influence the predictive capabilities of AI. Investigating this mediation helps determine whether improvements in data quality strengthen the connection between AI implementation and enhanced forecasting results.

To find out if data dependence and data quality in order affect how well AI helps with forecasting, the study looks at the steps from using AI to getting more accurate forecasts. This process involves several important factors in how things operate. The goal is to understand a clear path where using AI first makes people rely more on data, which then highlights how important good data quality is. By looking at this whole process, the research gives a full picture of how AI improves supply chain predictions in Pakistan’s specific retail and manufacturing areas.

1.6 Research Questions

Does the implementation of Artificial Intelligence enhance forecasting accuracy among supply chain professionals in Pakistan? Accurate demand forecasting is very important for efficient supply chain operations, as it affects how inventory is managed, how production is planned, and how satisfied customers are. This question looks into whether using AI tools like predictive analytics, machine learning algorithms, and automated forecasting systems can greatly increase forecast accuracy in Pakistan's manufacturing and retail industries. It also seeks to understand the real-world effects of adopting AI in places where technology infrastructure and data availability might not be very reliable.

Does data dependency serve as a mediator in the relationship between AI and forecasting accuracy? AI systems are inherently dependent on structured, timely, and continuous data streams. This question explores whether the extent to which organizations rely on data (data dependency). The study looks at how AI affects the accuracy of forecasts. By looking at this connection, the research wants to show how AI creates value through its operations. It explains that the advantages of AI might not be straightforward, but depend on having strong data practices in place.

Does data quality act as a mediator between AI and forecasting accuracy? Even with advanced AI systems, poor-quality data such as incomplete, outdated, or inconsistent information can undermine forecasting outcomes. This question assesses whether the quality of data mediates the impact of AI on supply chain forecasting accuracy. It highlights that companies need to do more than just use AI; they also have to make sure their data is accurate, useful, and thorough so they can get the most out of using AI for predictions.

Do data dependency and data quality sequentially mediate the impact of AI on forecasting accuracy? The connection between AI and how accurate forecasts are might be more complicated than just one direct or indirect influence. This question investigates a sequential mediation model where AI adoption first increases reliance on data, which then necessitates high data quality to achieve accurate forecasts. Understanding this sequential mechanism can provide deeper insights into how AI contributes to operational efficiency and help managers prioritize interventions that strengthen both data management and technology adoption practices.

Overall, these research questions collectively aim to bridge gaps in existing literature by integrating AI adoption, data dependency, and Data quality in a full model that shows how Pakistan's supply chain sectors really work.

- Does the use of AI lead to improved forecasting accuracy among supply chain professionals in Pakistan?
- Does data dependency mediate the relationship between AI and forecasting accuracy?
- Does data quality mediate the relationship between AI and forecasting accuracy?
- Do data dependency and data quality sequentially mediate the relationship between AI and forecasting accuracy?

1.7 Significance of Study

This study is important for both people working in the supply chain field and researchers in Pakistan. It looks at how Artificial Intelligence (AI) affects the accuracy of predictions. it provides supply chain managers with practical insights into how technological innovations can enhance operational efficiency. In particular, the study emphasizes the critical roles of data dependency and data quality in determining the success of AI implementation. Understanding these relationships equips decision-makers to implement AI strategically, ensuring that investments in technology are complemented by robust data infrastructure, systematic data governance, and a culture that prioritizes accurate and timely information. These measures can help organizations mitigate common operational challenges such as overstocking, stockouts, inefficient resource allocation, and delayed decision-making, ultimately leading to improved service delivery and customer satisfaction.

Furthermore, this research represents the first empirical effort in Pakistan to examine the simultaneous and sequential relationships between AI, data dependency, data quality, and forecasting accuracy through the theoretical lens of the COR theory. By applying COR theory, the study highlights how organizations must effectively manage and protect their critical resources, in this case, technological and informational resources, to achieve superior performance. The serial mediation framework used in this study helps to better understand how AI, as a technology, works with factors like data dependence and data quality to actually improve forecasting results. This approach extends beyond existing literature, which largely focuses on the technical capabilities of AI, by emphasizing the behavioral and operational mechanisms that mediate its effectiveness.

In addition to its theoretical contributions, the study has strong practical implications for organizations operating in emerging markets. It sheds light on the unique socio-economic, infrastructural, and cultural conditions of Pakistan that may influence How well AI works in managing the supply chain. For example, there are problems with not having enough data available, variability in digital literacy, and inconsistent adherence to data standards can significantly affect the outcomes of AI-based forecasting. By providing insights into these contextual factors, the study enables managers to tailor AI adoption strategies that are realistic, effective, and sustainable in the local environment. These results can help create better ways to design programs that make data gathering more efficient, improve the quality of data, and make better use of AI to increase the accuracy of predictions.

Moreover, the research contributes to future academic endeavors by opening new avenues for AI-related studies in emerging markets. It provides a foundation for comparative studies between developed and developing economies, examining how contextual differences influence the relationship between AI, data quality, and operational performance. Researchers can build on this study to explore additional mediating or moderating variables, such as organizational culture, employee skills, or technological readiness, that may further explain variations in AI effectiveness.

Finally, the outcomes of this study have policy implications as well. Policymakers and industry regulators can utilize these insights to establish guidelines, frameworks, and support mechanisms that encourage effective AI adoption in supply chains. Promoting standards for data quality, incentivizing technological investments, and facilitating knowledge-sharing initiatives can significantly enhance the efficiency, competitiveness, and resilience of Pakistan's manufacturing and retail sectors. These results can help create better plans for improving how data is collected, making the data more accurate, and using AI more effectively to get better predictions. supported by high-quality data and structured data management practices, can transform forecasting processes, offering substantial benefits for managers, researchers, and policymakers alike.

1.8 Structure of Thesis

This thesis is made up of five connected chapters, each helping to fully explain the research topic. Chapter 1 is the introduction, which gives a detailed background about the study, shows where there are gaps in current knowledge, and clearly states the problem being studied. It also lists the research goals, questions, and why the study is important, which sets up the rest of the thesis.

Chapter 2 looks at existing research in depth, carefully examining studies related to Artificial Intelligence, how much data is needed, the quality of data, and how well forecasts work in supply chains.

This chapter also sets up the main ideas and theories that guide the study, with a special focus on the Conservation of Resources (COR) theory, which helps explain the relationships explored in this research.

Chapter 3 describes the method used to do the research. It explains the research philosophy, strategy, and design, followed by details on data collection methods, sampling techniques, and the analytical procedures employed. This chapter ensures transparency and rigor, providing a clear roadmap for how the research objectives will be addressed empirically.

Chapter 4 shows the results and analysis of the data, including statistical tests that look at how Artificial Intelligence, data dependency, data quality, and forecasting accuracy are connected. This chapter explains the findings based on the research questions and the theory used, giving clear, evidence-based information about how AI is being adopted in Pakistan's supply chain industry.

Chapter 5 goes into more detail about the findings, discussing both the theoretical and real-world impacts. It also talks about the study's limitations, gives advice for business leaders and government officials, and ends with ideas for future research. Collectively, these chapters provide a cohesive and structured examination of how AI, supported by high-quality data and effective data management, influences forecasting accuracy in the manufacturing and retail supply chains of Pakistan.

Chapter 2

Literature Review and Theoretical Framework

2.1 Artificial Intelligence (IV)

Artificial Intelligence is the ability of computer systems to do things that usually need a human's intelligence, like looking at data, finding patterns, learning from experience, and making choices. In the context of supply chain management, AI has become a transformative tool, enabling organizations to process large volumes of structured and unstructured data to generate actionable insights in real-time (Wamba et al., 2020). AI is used in supply chains for tasks like predicting demand, managing stock, finding the best delivery paths, choosing the right suppliers, and planning logistics. For example, predictive analytics helps managers guess how much product will be needed, and machine learning finds hidden trends that are hard to see with usual methods. Additionally, AI also enables real-time decision-making and scenario analysis, helping managers respond to sudden changes in demand, disruptions in supply, or unexpected market shifts, which increases overall operational agility and resilience (Choi et al., 2020; Ivanov et al., 2021).

In Pakistan, the adoption of AI in manufacturing and retail is still emerging. While some larger firms have begun integrating AI-based solutions for demand planning and inventory control, small and medium-sized enterprises (SMEs) often face barriers such as limited technical expertise, insufficient digital infrastructure, and inconsistent data collection practices (Sharma & Hussain, 2021). Despite these challenges, AI offers significant benefits. By automating routine decisions and analyzing complex datasets, AI improves agility, reduces human error, and enhances responsiveness to market volatility. Additionally, AI adoption supports strategic objectives such as operational efficiency, cost reduction, and customer satisfaction, particularly in dynamic retail environments where consumer behavior changes rapidly (Gunasekaran et al., 2017).

Moreover, AI can contribute to sustainable supply chain practices by optimizing resource use, reducing waste, and improving overall supply chain visibility, which further strengthens the competitive position of firms adopting these technologies (Dubey et al., 2022; Makridakis et al., 2020). However, the successful implementation of AI requires more than just technology acquisition. Firms must develop robust data management systems, invest in employee training, and ensure alignment between AI tools and business processes. Without these complementary resources, the full potential of AI cannot be realized, and organizations may struggle to achieve improved forecasting performance.

Furthermore, leadership support and organizational culture that encourage innovation are critical to effectively leveraging AI, as these factors influence adoption success and the ability to integrate AI insights into strategic decision-making processes (Choi et al., 2020; Dubey et al., 2022).

2.2 Forecasting Accuracy (DV)

Forecasting accuracy measures how closely predicted values correspond to actual outcomes, particularly in terms of demand planning and inventory management. High forecasting accuracy is crucial for supply chain efficiency, as it directly affects inventory levels, manufacturing schedules, customer service, and normal operational expenses (Mentzer & Moon, 2004). Accurate forecasts enable organizations to minimize waste, reduce stockouts, optimize resource allocation, and maintain high service levels.

Additionally, accurate forecasting reduces the financial risks associated with excess inventory or stockouts and helps firms allocate resources efficiently, ensuring a smoother supply chain flow even under volatile market conditions (Wamba et al., 2020; Kaur & Singh, 2021).

Several factors influence forecasting accuracy, including the sophistication of predictive models, availability and quality of historical data, market volatility, how well the supply chain can adjust to changes in what people want to buy. Traditional forecasting methods often rely on historical sales data and expert judgment, which may fail to capture sudden market shifts or seasonal variations (Wamba et al., 2020). AI, when combined with structured, High-quality data can help improve forecasting accuracy by identifying complex patterns and offering predictions that are almost real-time.

Moreover, combining AI with human expertise in hybrid forecasting approaches can further enhance accuracy, allowing firms to adjust predictions based on managerial experience or unforeseen market disruptions, which is especially useful in emerging economies like Pakistan (Makridakis et al., 2020; Dubey et al., 2022).

This is especially important in Pakistan's manufacturing and retail industries., achieving high forecasting accuracy is particularly challenging. Organizations often contend with inconsistent data collection practices, fragmented supply chains, and varying levels of technological adoption. Therefore, understanding how AI, data dependency, and data quality interact to influence forecasting accuracy is crucial. By examining these relationships, organizations can identify strategies to improve how things work, save money, and make customers happier, getting accurate predictions is very important in supply chains that use AI.

In addition, improving forecasting accuracy through AI enables better strategic planning, reduces operational risks, and improves customer trust by ensuring product availability aligns with market demand, which enhances long-term competitiveness (Choi et al., 2020; Ivanov et al., 2021).

2.3 Mediating Variables:

2.3.1 The Relationship between AI and Forecasting Accuracy

Artificial Intelligence helps companies handle large amounts of different types of data quickly, allowing them to find difficult patterns and make predictions almost instantly. In the context of supply chain operations, these capabilities have transformative implications. For instance, AI helps improve predictions about how much of a product will be needed in the future by looking at past sales, trends during different times of the year, and how the market is changing. This makes it easier to guess what people will want to buy next. It improves inventory management by identifying optimal stock levels, reducing overstocking or stockouts, and lowering holding costs. Additionally, AI facilitates route optimization in logistics by analyzing traffic patterns, delivery schedules, and transportation constraints to ensure timely deliveries at minimal costs. Beyond operational efficiency, AI enhances customer service by anticipating consumer needs, personalizing offerings, and responding swiftly to changes in demand or supply disruptions.

Furthermore, AI enables organizations to perform predictive scenario analysis, risk assessment, and real-time monitoring of supply chain activities, which increases operational resilience and improves decision-making under uncertainty (Choi et al., 2020; Ivanov et al., 2021).

By using AI to handle everyday tasks and offer powerful analysis tools, it greatly cuts down on mistakes people make and slows down decisions. This helps improve how well operations run and allows supply chains to handle sudden changes in the market better. Sudden demand fluctuations, and unforeseen disruptions. For emerging economies like Pakistan, where supply chains often face infrastructural and informational challenges, AI offers a strategic advantage by allowing firms to make data-driven, timely decisions despite such constraints (Wamba et al., 2020).

From a practical perspective, firms leveraging AI can achieve faster response times, better alignment of supply and demand, and reduced operational costs, which ultimately strengthens competitiveness in dynamic market environments (Dubey et al., 2022; Makridakis et al., 2020).

From the perspective of Conservation of Resources (COR) theory, AI represents a critical technological resource that organizations can leverage to enhance performance. However, its effectiveness is contingent upon integration with other supporting resources, including robust data systems, reliable IT infrastructure, and skilled personnel capable of managing and interpreting AI-generated insights. Without these complementary resources, the potential of AI remains underutilized, and improvements in forecasting accuracy may be limited. Therefore, organizations that successfully adopt AI, while ensuring supportive infrastructure and resource management, are likely to experience significant improvements in forecasting performance, translating into more accurate, timely, and actionable predictions.

Hypothesis 1 (H1): Artificial Intelligence is positively associated with forecasting accuracy in supply chain operations.

2.3.2 Data Dependency (M1)

Data dependency means how much AI systems depend on having constant, organized, and up-to-date data to work well and make accurate forecasts. In supply chain operations, AI algorithms especially predictive analytics and machine learning models require frequent, high-quality data inputs from multiple touchpoints, including sales records, inventory levels, supplier information, transportation logs, and customer interactions. The quality, frequency, and comprehensiveness of these data streams directly influence the system's ability to detect patterns, anticipate demand fluctuations, and produce reliable forecasts (Gunasekaran et al., 2017). Without a steady and well-integrated flow of relevant data, even sophisticated AI models may produce suboptimal predictions, resulting in stockouts, overstocking, or inefficiencies in distribution and production planning.

In addition, emerging technologies like cloud computing, IoT-based sensors, and real-time monitoring platforms enhance data dependency by ensuring continuous, accurate, and timely data flow, which strengthens AI forecasting capabilities (Dubey et al., 2022; Sharma & Hussain, 2021). From the perspective of COR theory, the effectiveness of AI as a technological resource is contingent upon the availability and proper management of complementary resources. Data dependency represents one such operational requirement, highlighting the reliance of AI systems on a consistent and high-quality data environment. When organizations maintain reliable data flows, AI can function as intended, improving forecasting accuracy and operational decision-making. Conversely, if data inputs are inconsistent, incomplete, delayed, or poorly structured, the AI system's potential is significantly constrained, leading to forecasting errors and reduced efficiency.

Therefore, data dependency is seen as a main factor that helps explain how the process works. which AI adoption translates into enhanced forecasting performance. It bridges the gap between technology implementation and operational outcomes, demonstrating that AI's impact is not solely determined by its algorithmic sophistication but also depending on how much timely and it has structured data inputs.

Hypothesis 2 (H2): Data dependency mediates the relationship between AI and forecasting accuracy.

2.3.3 Data Quality (M2)

Data quality refers to the overall situation and reliability of facts used by AI systems, encompassing dimensions inclusive of accuracy, completeness, consistency, timeliness, and relevance (Wang & sturdy, 1996). In supply chain operations, good data helps AI models understand past patterns, spot trends, and create accurate and useful predictions. For instance, complete and accurate sales data, real-time inventory records, and reliable supplier information allow AI algorithms to predict demand fluctuations effectively, optimize stock levels, and improve resource allocation. Conversely, poor-quality data such as missing transactions, duplicate records, inconsistent reporting formats, or outdated information can mislead AI systems, resulting in biased or erroneous predictions. Such inaccuracies may cause overstocking, stockouts, inefficient production schedules, and ultimately, reduced customer satisfaction.

Moreover, implementing robust data quality management practices, such as automated validation checks, data cleaning processes, and continuous monitoring, ensures that AI systems function at their highest predictive capability. That is specifically vital in dynamic markets where even small inaccuracies can lead to big operational losses and patron dissatisfaction (Dubey et al., 2022; Kaur & Singh, 2021).

From the perspective of COR theory, AI considered as a valuable organizational resource whose effectiveness is dependent on the condition of complementary resources. In this context, data quality acts as a critical supporting resource. By maintaining accurate, complete, and consistent data, organizations not only protect the integrity of their AI systems but also maximize their predictive potential. Effective management of data quality ensures that the AI resource can be fully leveraged, resulting in enhanced forecasting performance. Thus, data quality is conceptualized as a mediating factor that explains how AI adoption translates into improved supply chain outcomes, bridging the gap between technology implementation and operational success.

Additionally, high-quality data supports better strategic planning, risk mitigation, and resource allocation by providing managers with trustworthy insights, allowing for faster and more confident decision-making, which strengthens overall supply chain resilience (Ivanov et al., 2021; Makridakis et al., 2020).

Hypothesis 3 (H3): Data quality mediates the relationship between AI and forecasting accuracy

2.3.4 Sequential Mediation of Data Dependency and Data Quality

The relationship between AI and forecasting accuracy is inherently multifaceted, extending beyond simple direct or indirect effects. While AI adoption provides advanced analytical skills, predictive modeling, and automation, its success relies upon heavily on the operational and supporting assets available within a corporation. One critical operational factor is data dependency, this describes how much AI systems depend on ongoing, organized, and up-to-date information from various places, like sales records, inventory systems, supplier databases, and customer interactions. When AI adoption increases, organizations often experience heightened data dependency, as these systems require a steady flow of accurate information to generate reliable forecasts (Gunasekaran et al., 2017).

Furthermore, AI-driven analytics platforms often require integration across multiple departments and external partners to maintain data dependency. Organizations that succeed in implementing such integrative data systems benefit from improved visibility across the supply chain, reduced delays in decision-making, and enhanced forecasting reliability (Dubey et al., 2022; Sharma & Hussain, 2021).

However, data dependency alone does not guarantee forecasting success. If the input data is of poor quality such as incomplete, inconsistent, outdated, or inaccurate information the AI system's predictive power is compromised, leading to suboptimal or misleading forecasts. In contrast, when high levels of data dependency are paired with high-quality data, AI can deliver precise and actionable insights, enabling organizations to optimize inventory levels, reduce stockouts, improve customer satisfaction, and respond effectively to market volatility (Wang & Strong, 1996; Wamba et al., 2020).

Moreover, ensuring sequential integration of data dependency and data quality creates a synergistic effect, where well-structured data flows enhance AI performance and high-quality data ensures the reliability of predictions. This combination supports continuous improvement in operational processes and strategic decision-making, especially in volatile and competitive markets (Choi et al., 2020; Ivanov et al., 2021).

This sequential interaction between AI, data dependency, and data quality aligns with the principles of Conservation of Resources (COR) theory, which posits that the effectiveness of a primary resource depends on the availability and management of complementary resources (Hobfoll, 1989). In this framework, AI functions as the primary organizational resource, while data dependency and data quality serve as essential operational and supporting resources. The theory suggests that the value generated by AI is realized only when these supporting resources are adequately managed and protected. Therefore, the relationship between AI and forecasting accuracy is best understood as a sequential mediation process: AI adoption increases reliance on structured data (data dependency), which then emphasizes the need for high-quality data to achieve accurate and reliable forecasting outcomes.

In addition, empirical studies indicate that organizations implementing this sequential approach achieve higher forecasting accuracy, improved operational efficiency, and stronger alignment between supply and demand, highlighting the critical importance of both operational and supporting resources in AI adoption (Dubey et al., 2022; Makridakis et al., 2020).

Hypothesis 4 (H4): Data dependency and data quality sequentially mediate the relationship between AI and forecasting accuracy.

2.4 Theoretical Foundations: Conservation of Resources Theory

The Conservation of Resources (COR) theory, formulated by Hobfoll (1989), provides a foundational framework to understand how individuals and organizations manage and protect valuable resources. According to the theory, resources encompass not only tangible assets, such as money or equipment, but also intangible assets, including knowledge, skills, social support, technology, and data. COR theory posits that when these resources are threatened, lost, or inadequately replenished, stress arises, which can negatively impact performance and organizational outcomes. Conversely, the accumulation and effective utilization of resources enhance resilience, adaptability, and overall effectiveness.

In supply chain management, Artificial Intelligence (AI) is a key technology. AI can handle large amounts of data, both organized and not, find patterns, and create predictions that help with making decisions. Specifically, AI facilitates demand forecasting, inventory optimization, supplier evaluation, and route planning, thereby increasing operational efficiency and reducing costs (Wamba et al., 2020). However, the COR theory shows that just using AI as a tool doesn't always lead to better results. Whether AI works well depends a lot on having other resources that help it function properly.

Two key supporting resources in this study are data dependency and data quality. Data dependency refers to the operational reliance on continuous, structured, and timely data inputs. AI systems, particularly those used in forecasting, cannot function effectively without a reliable inflow of data from multiple sources such as sales records, inventory systems, logistics platforms, and customer behavior analytics (Gunasekaran et al., 2017). High levels of data dependency imply that organizations must have robust data integration mechanisms, real-time data pipelines, and advanced IT infrastructure. Without these systems, the predictive capabilities of AI may be compromised, leading to inaccurate forecasts and suboptimal decision-making.

Data quality shows how good, dependable, and helpful the data is when it's being used. High-quality data is characterized by accuracy, completeness, consistency, timeliness, and relevance (Wang & Strong, 1996). Even with sophisticated AI algorithms, poor-quality data can undermine predictive accuracy, resulting in errors such as overstocking, stockouts, and misallocation of resources. In COR terms, poor data quality represents a depleted resource that diminishes the effectiveness of AI as a technological asset. This highlights that resources do not function in isolation; the value of one resource depends on the presence and condition of other supporting resources.

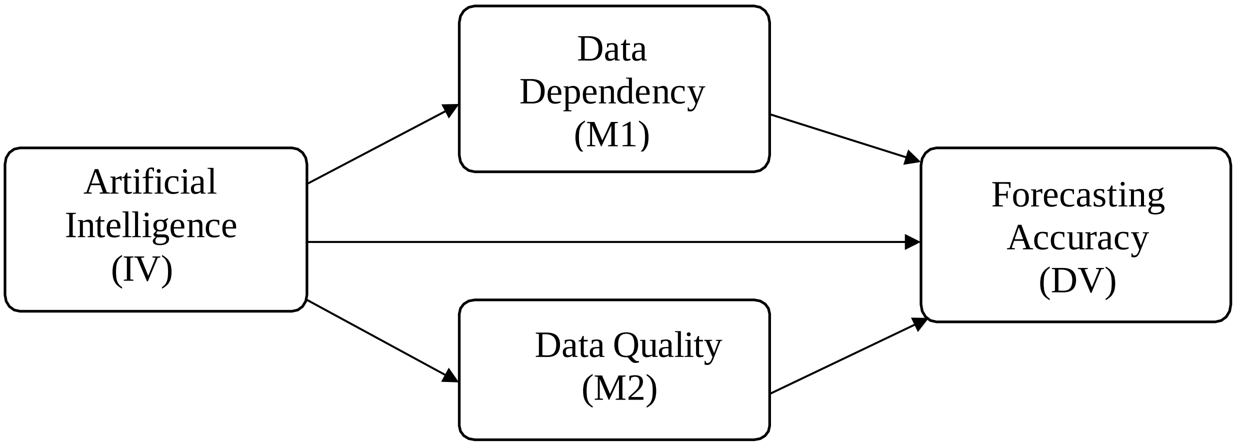
Applying COR theory to the context of AI adoption in Pakistan's manufacturing and retail sectors provides several important insights. First, it emphasizes that AI adoption alone is insufficient to guarantee forecasting success. Organizations must ensure that critical supporting resources, particularly high-quality data, are available and adequately maintained. Second, the theory explains why an imbalance between resource availability and resource dependency can negatively affect outcomes. For example, if an organization relies heavily on AI for forecasting (high data dependency) but lacks robust data governance and quality assurance processes, the organization may experience resource depletion, operational inefficiencies, and reduced forecasting accuracy. Third, COR theory underscores the importance of resource accumulation and protection. By investing in technological infrastructure, data governance, and skilled personnel, organizations can enhance the effectiveness of AI and ensure sustainable improvements in operational performance. In practical terms, the application of COR theory in this study supports the proposed sequential mediation model. AI adoption increases reliance on structured data (data dependency), which in turn highlights the importance of ensuring high data quality. Only when both supporting resources are effectively managed can AI deliver accurate forecasts and improve operational efficiency. This perspective bridges the gap between technology-focused approaches and resource-based considerations, demonstrating that the benefits of AI are contingent on the broader organizational ecosystem.

Furthermore, the COR framework is particularly relevant for emerging markets such as Pakistan, where organizational and infrastructural resources may be constrained. Challenges such as limited digitization, fragmented logistics, inconsistent data governance practices, and varying levels of technological readiness can influence how effectively AI can be leveraged in supply chain operations. By viewing AI as a resource whose effectiveness depends on complementary resources, COR theory provides a comprehensive lens to understand these contextual challenges and to design strategies that optimize forecasting performance despite operational limitations.

In summary, the Conservation of Resources theory not only explains why AI alone cannot ensure improved forecasting outcomes but also highlights the critical roles of data dependency and data quality in mediating AI's effectiveness. This theoretical lens validates the importance of examining sequential resource-based mechanisms, providing both a conceptual and practical framework for understanding AI adoption in Pakistan’s manufacturing and retail supply chains. It reinforces the idea that resource accumulation, protection, and strategic deployment are fully realize the potential of advanced technological systems in real-world operations.

2.5 Theoretical Framework

Figure 1: Theoretical Framework



Chapter 03

Research Methodology

Introduction

This chapter explains the method used to study how AI affects forecasting accuracy in Pakistan's manufacturing and retail industries. It focuses on how data dependency and data quality act as middle factors that influence this impact. The study uses the COR theory to explain why AI is considered a useful resource for organizations and how its success depends on other important factors like accurate and timely data. The research approach is designed to make sure the results are trustworthy, consistent, and relevant to the situation in Pakistan. This helps add important knowledge to academic research and also supports real-world use in supply chain management.

The need for a thorough and careful approach comes from how complicated the research problem is. Even though a lot of studies have looked at how AI can improve supply chain performance through technology, there is still a big gap in understanding the practical and situation-based factors that affect how well AI works. In particular, the roles of data dependency and data quality have been underexplored, especially in emerging economies such as Pakistan, where technological infrastructure, digital literacy, and organizational data governance practices differ markedly from those in developed countries. Addressing these gaps requires a carefully structured research approach capable of capturing nuanced relationships and providing reliable insights into real-world operations.

Given the multifaceted nature of the research objectives, the methodology has been developed to systematically Look at both the straight and the hidden ways that using AI affects how accurate forecasts. The study seeks to determine not only whether AI improves forecasting outcomes but also how this effect is mediated by the reliance on structured data and the quality of information utilized by AI systems. This method helps to better understand how AI creates value in supply chain operations. Additionally, the study’s methodological design accounts for the unique challenges faced by organizations in Pakistan, including inconsistent data availability, fragmented supply chain systems, and varying levels of technological adoption. By grounding the research in the specific socio-economic and operational context of Pakistan, the methodology enhances the relevance and applicability of the findings.

To achieve these objectives, this chapter outlines the research philosophy guiding the study, the methodological approach, and the overall research design. It further elaborates on the population and sampling strategies, The process of creating and checking the research tool, along with the steps used to gather data, is explained. Ways to make sure the tool works well and gives accurate results are covered. The methods used to analyze the data and check the research ideas are also described. Additionally, the ethical issues involved and the steps taken to keep the research honest and private are included.

By establishing a clear and rigorous methodological framework, this chapter provides the foundation for the empirical analysis presented in subsequent chapters. The methodology not only facilitates the testing of theoretical relationships derived from COR theory but also ensures that the study offers useful ideas that help professionals apply AI properly in supply chain work. In the end, this research tries to connect theory with real-world use by showing how AI can be used effectively when supported by reliable data systems and high-quality information, can enhance forecasting accuracy, operational efficiency, and organizational performance in Pakistan's manufacturing and retail sectors.

3.1 Research Philosophy

Research philosophy is a collection of beliefs, ideas, and rules about what knowledge is, how the world works, and how to gather and understand information. It acts as the basic guide for how research is planned, carried out, and analyzed. In studies related to business and management, there are several common research philosophies, such as positivism, interpretivism, realism, and pragmatism. Each of these has different ideas about what counts as true knowledge and how it can be found. Positivism believes in objectivity, measurable facts, and using science-like methods to find cause and effect relationships. On the other hand, interpretivism is more about understanding people's personal experiences and the social situations they are in, and it usually uses methods that focus on quality rather than quantity. Realism combines elements of both, recognizing that observable phenomena exist but are influenced by contextual factors. Pragmatism prioritizes practical problem-solving and may integrate multiple methods depending on research needs.

In this study, a positive approach has been taken because the main goal is to look at real connections between Artificial Intelligence, data dependency, data quality, and forecasting accuracy in the supply chain sector. The research seeks to test clearly defined hypotheses using measurable variables and statistical analysis. By applying a positivist lens, the study emphasizes objectivity, replicability, and empirical verification, ensuring that the results are based on observable evidence rather than subjective interpretations. This philosophical orientation aligns with the quantitative research design, enabling a systematic evaluation of how AI adoption affects forecasting outcomes under varying conditions of data dependency and quality. Positivism is particularly suitable in this context as it allows for the identification of causal links and provides robust, generalizable insights that can guide managerial decision-making.

3.2 Research Purpose

The goal of a research study sets the main direction of the work and affects how the research is done, how data is gathered, and how the results are analyzed. In business research, studies are usually grouped into three types: exploratory, descriptive, and causal. Exploratory research is used when little is known about a topic, and the main goal is to learn more and come up with possible ideas or questions to study further. Descriptive research is used to give a clear picture of a situation, group of people, or event, but it doesn't look for reasons why things happen. Causal research is used to find out how one thing affects another and to test if there is a direct link between them.

The present study is causal in nature because it investigates whether the implementation of Artificial Intelligence directly influences forecasting accuracy in supply chain operations, and whether this relationship is mediated by data dependency and data quality. The causal purpose allows the study to move beyond mere description and towards understanding the mechanisms through which AI adoption translates into improved operational outcomes. By employing a theoretically informed model based on the COR theory, the research examines how a technological resource (AI) interacts with operational resources (data dependency and data quality) to impact forecasting performance. Understanding these causal pathways is critical for managers and policymakers, as it gives practical ideas on how to use AI in a way that improves the efficiency of the supply chain.

3.3 Research Approach

The way a study is done, called the research approach, is how you go from ideas to real-world observations. In social science, there are two main ways to do this: inductive and deductive. Inductive starts with looking at what happens in real life and then creates ideas or theories based on what is found. Deductive starts with already known ideas or guesses and checks if they are true in real situations.

This study uses the deductive method because it follows the COR theory, which provides a theoretical lens to understand the interplay between AI, data dependency, data quality, and forecasting accuracy. Hypotheses were developed based on existing literature, and structured data collection was designed to test these relationships empirically. The deductive approach ensures that the study remains systematic and theory-driven, allowing the results to either support or challenge existing knowledge. This approach also aligns with the positivist philosophy, emphasizing objectivity, hypothesis testing, and quantitative analysis. Using deductive reasoning ensures that the study can produce generalizable findings relevant to other similar emerging market contexts.

3.4 Research Strategy

Research strategy is a detailed plan that explains how data is gathered, examined, and understood. In business research, common methods include case studies, ethnography, grounded theory, experiments, and surveys. Each method has its own strengths and weaknesses, which depend on the research questions and the type of data being collected. Case studies give deep insights into specific organizations but may not apply to other situations. Experiments can show cause and effect but might not reflect real-life conditions. Surveys, however, help collect consistent information from many people and are especially useful in studies that test clear hypotheses.

In this study, a survey-based quantitative approach was chosen. This method works well because it allows researchers to collect organized data from supply chain experts in various manufacturing and retail companies in Pakistan. By using a standardized questionnaire, the study ensures consistency in responses, facilitating statistical analysis to test the hypothesized relationships. A quantitative strategy lets you measure things like how much AI is used, how much data is relied on, how good the data is, and how accurate the forecasts are. This helps in thoroughly checking how these things are connected to each other.

3.5 Time Horizon

Time horizon refers to the period during which data is gathered and studied. In business research, there are two main types of time horizons: cross-sectional and longitudinal. A cross-sectional design collects data at one specific time, giving a quick view of the variables and how they connect. Longitudinal research, on the other hand, gathers data over a longer time to see how things change, trends develop, or patterns emerge.

This study uses a cross-sectional time horizon. Data is collected at one moment to look at how AI adoption, reliance on data, and data quality currently affect forecasting accuracy in supply chains. A cross-sectional approach works well here because of limited time and resources, and it gives enough understanding of existing patterns and connections. Although longitudinal studies can show how things change over time, a cross-sectional method is better for testing the cause-and-effect ideas in this study, especially since the research involves a large group and focuses on clear, observable results.

3.6 Data Collection Method

Data collection is a very important part of research because the quality and trustworthiness of the results depend on how accurate the data is. In quantitative research, people often use tools like surveys, experiments, or structured interviews. Surveys are especially useful when studying many factors or a large group of people, because they help make sure the information is gathered in a consistent way and can be compared easily.

In this study, data was gathered using a structured questionnaire given to professionals in the supply chain in Pakistan's manufacturing and retail industries. Surveys were chosen because they allow for quickly collecting a lot of data in a uniform way, making it easier to analyze with statistical methods. Additionally, the survey format enables the researcher to capture both the demographic characteristics of respondents and their perceptions of AI adoption, data dependency, data quality, and forecasting accuracy. Administering surveys in person also allowed the researcher to clarify any ambiguities, encourage participation, and improve response rates.

3.7 Questionnaire Development

The questionnaire for this study was made with care to include all important factors and make sure it was clear and dependable. It was split into two parts. The first part asked for basic details like age, gender, job title, years of experience, and the industry they work in, which helped set the background for the study. The second part focused on the main topics being studied: using AI, how much they rely on data, how good the data is, and how accurate their forecasts are.

Each question about these topics was taken from existing research scales but adjusted to fit the situation in Pakistan’s supply chain. For example, questions about AI were based on Wamba et al. (2020), data reliance came from Gunasekaran et al. (2017), and data quality was adapted from Wang & Strong (1996). Every question used a five-point scale from "Strongly Disagree" to "Strongly Agree" so people could easily understand and respond. The questionnaire was checked by academic advisors, master’s students, and ten professionals from the industry to make sure it was accurate, clear, and relevant. Based on their suggestions, changes were made to make it easier to read, less confusing, and more realistic for how supply chains work in Pakistan.

3.8 Measures

In this study, measuring the variables is very important to make sure the results are both accurate and trustworthy. The constructs Artificial Intelligence (AI), data dependency, data quality, and forecasting accuracy were measured using structured scales adapted from previous studies. AI adoption was assessed based on the extent of AI integration in forecasting, inventory management, and operational decision-making (Wamba et al., 2020). Data dependency measured the reliance of AI systems on continuous and structured data inputs from multiple sources, including sales, inventory, and customer systems (Gunasekaran et al., 2017). Data quality was measured using dimensions such as accuracy, completeness, consistency, and timeliness (Wang & Strong, 1996). Forecasting accuracy captured the degree to which predicted values aligned with actual outcomes (Mentzer & Moon, 2004). Every item was checked using a 5-point system that started with "Strongly Disagree" and ended with "Strongly Agree".

3.9 Unit of Analysis

In this study, the main thing being studied is the individual professional who works in supply chain areas of manufacturing and retail companies in Pakistan. The data is gathered and looked at based on these people. These individuals include supply chain managers, procurement officers, inventory planners, demand forecasting specialists, and logistics coordinators who are directly responsible for making decisions related to forecasting, inventory management, and operational planning.

Looking at individual cases helps the study get a clearer understanding of how AI is actually being used, the extent to which employees rely on data (data dependency), and their perceptions of data quality in daily operations. Individual-level analysis is particularly appropriate because AI adoption, data practices, and Forecasting results can be very different depending on the job someone has, how experienced they are, and how much power they have when making decisions. For example, a supply chain manager may have access to strategic-level AI tools and dashboards, whereas operational staff may interact primarily with transactional or real-time data systems.

Looking at the data at the individual level helps the study spot patterns and connections that might not show up when looking at the whole organization. This method makes sure the results show real behavior, experiences, and feelings of the people who work with AI systems and data in their jobs. By understanding what happens at the individual level, the research can better explain how effective AI is, how much people rely on data, and why good data quality is important for making better predictions in Pakistan's manufacturing and retail supply chains.

3.10 Population

The population in a research study is the whole group of people, teams, or things that fit certain conditions and from which information can be gathered. In this study, the population includes every person working in the supply chain in the manufacturing and retail industries in Pakistan. This includes employees involved in planning, procurement, inventory management, logistics, demand forecasting, and other related functions. These professionals are directly involved in decision-making processes that affect forecasting accuracy, data management, and the adoption of technological tools such as AI.

Pakistan’s manufacturing sector spans textiles, food processing, electronics, and automotive industries, among others, while the retail sector ranges from large retail chains to e-commerce platforms and SMEs. According to estimates, there are over 50,000 professionals working in these sectors nationwide. By focusing on this group, the study makes sure the results are useful for using AI in real supply chain work. Choosing this group is important because it includes different types of companies and how much they use technology, and data management practices, reflecting the diversity and challenges present in emerging markets like Pakistan.

3.11 Sampling Technique

Sampling is when you pick a smaller group from a bigger group so that this smaller group shows what the bigger group is like. It's important to choose the right way to pick this smaller group so that the information you get is trustworthy, correct, and can be applied to the whole group. In this study, a multi-stage cluster sampling technique is employed, combining elements of convenience and purposive sampling to balance feasibility with representativeness.

In the first stage, Pakistan is divided into geographic regions to ensure coverage of multiple industrial and commercial hubs. This geographic clustering captures regional variations in technology adoption, supply chain practices, and organizational structures. In the second stage, companies located in Islamabad are selected based on their registration in industrial zones such as I-9, Blue Area, and other commercial districts, which are known for hosting manufacturing and retail firms.

In the third stage, employees working in the supply chain departments of these selected firms are approached. In these groups, the researcher uses convenience sampling to pick people who are easy to reach and willing to take part. This method helps gather information quickly while still including a variety of job types, work organizations, and levels of experience. By using a multi-stage cluster sampling approach, the study makes sure the group selected is similar to the whole population it's studying, while also staying realistic and doable based on available time and resources.

3.12 Sample Size

Sample size means the number of people from whom information is gathered. It is very important because it affects how reliable, accurate, and applicable the research results are. When there are more people in the sample, it usually means the results are more trustworthy and there is a better chance of finding important connections between different factors.

In this study, the group we are looking at includes more than 50,000 people working in supply chain jobs in Pakistan's manufacturing and retail industries.

According to the advice from Krejcie and Morgan in 1970, for a group this big, at least 384 people should be included in the study to be 95% sure of the results, with only a 5% chance of error. So, the study will include 384 participants to make sure the group is well represented in terms of company size, industry type, and job roles.

This number of participants also makes it possible to do strong statistical work, like Structural Equation Modeling or regression analysis. These methods need enough data points to properly test ideas and estimate values. By following these guidelines, the study makes sure its results are both dependable and can be applied to the larger group of supply chain professionals in Pakistan.

3.13 Data Collection Procedure

The process for collecting data explains the organized steps taken to get information from the chosen participants in a way that ensures it is correct and reliable, consistency, and ethical compliance. In this study, access to supply chain professionals was sought through formal communication with supply chain managers and HR departments in the selected firms. These contacts facilitated scheduling and distribution of questionnaires to ensure a smooth data collection process.

The survey was administered in person using paper-based questionnaires. This method allowed the researcher to provide immediate clarifications, minimize misunderstanding of items, and increase the response rate. Participants were told about the purpose of the study, promised that their information would be kept private, and made clear that they could choose to take part or not. Completed questionnaires were collected in sealed envelopes to maintain anonymity and data integrity.

To further enhance data quality, the researcher conducted follow-ups with participants who did not return questionnaires immediately, ensuring a higher response rate. The procedure was designed to capture responses efficiently while reflecting the real-world perceptions and experiences of supply chain professionals regarding AI adoption, data dependency, data quality, and forecasting accuracy.

3.14 Ethical Considerations

Ethical considerations are very important in academic research to protect people's rights, keep the research honest, and build trust. This study followed all the ethical rules carefully during every step of the research. Everyone who took part gave their permission before joining, making sure they knew what the study was about, that their participation was optional, and that they could stop at any time without any problems. To keep their information private, responses were made anonymous, and all data was kept safe in locked digital files with passwords. Paper forms were kept in locked cabinets that only the researcher could access.

Participants were told their answers would only be used for learning purposes and would not influence their job or career. No money or gifts were given, so people could take part freely without being forced. The way the study was set up and how data was collected were checked and approved by the academic leader to make sure everything met ethical standards.

By using these protective measures, the study showed respect for the people involved, kept their information safe, and followed the best practices for honest research. This helped make the study results more reliable and trustworthy.

CHAPTER 04

RESULTS

Introduction

This chapter shares the results of the study, following a clear and organized way to look at the data collected. The main goal of this research was to look at how Artificial Intelligence (AI) affects the accuracy of predictions in supply chain activities, while also looking at how data dependency and data quality play a role in this process. Since this study is based on numbers, we used SPSS to do some basic analysis, check if the tools we used were reliable, and see how variables are connected. We also used AMOS for Structural Equation Modeling (SEM) to check our ideas about how things are connected. SEM was chosen because it can look at both direct and indirect ways that things are connected, which is important for understanding the model we proposed in this study.

The chapter is broken into five main parts. The first part gives an overview of who the people in the study were, so we can understand who we're looking at and if the group is representative. The second part checks if the tools we used to measure things work well and give accurate results. The third part looks at how well the model we created fits with the actual data, using different measures to see if it's a good match. The fourth part shows the results of testing our ideas, including direct effects, indirect effects, and how these effects work in a sequence. Finally, the chapter ends with explaining what the results mean, based on the ideas and goals of the study.

4.1 Demographic Characteristics of Respondents

Descriptive Statistics of Respondents (N = 384)

Demographic Variable	**Category**	**Frequency**	**Percentage (%)**
Gender	Male	238	62.0
	Female	146	38.0
Age (Years)	26–35	173	45.1
	36–45	123	32.0
	Below 26 / Above 45	88	22.9
Education Level	Bachelor's Degree	196	51.0
	Master's Degree	142	37.0
	MPhil / Other Professional Qualification	46	12.0
Work Experience	Less than 5 years	69	18.0
	5–10 years	204	53.1
	More than 10 years	111	28.9
Job Role	Operations / Supply Chain Officer	98	25.5
	Logistics / Inventory Management	121	31.5
	Forecasting / Planning Analyst	87	22.7
	Senior Operations / Decision-Making Roles	78	20.3
Industry Sector	Manufacturing	230	59.9
	Retail	154	40.1

Table 1: Descriptive Statistics of Respondents

Interpretation:

The study received a total of 384 valid responses, which met the recommended sample size for generalizability and robust statistical analysis. Respondents represented diverse positions within retail and manufacturing supply chains in Pakistan, reflecting the target population of professionals involved in operational decision-making, logistics, inventory management, and forecasting activities.

Among the participants, 62% were male, while 38% were female, indicating a moderate gender representation across the supply chain workforce. Age distribution revealed that 45% of respondents were between 26 and 35 years, 32% were between 36 and 45 years, and the remaining 23% fell outside these age ranges. This distribution suggests a workforce that is relatively young to mid-career, with substantial exposure to technological tools and modern supply chain practices. In terms of work experience, 53% of participants reported having 5–10 years of professional experience, while 29% had more than 10 years. This indicates a significant proportion of respondents with considerable exposure to supply chain operations and forecasting activities, Enhancing the credibility and relevance of the collected data. About 60% of the respondents were employed in the manufacturing sector, while the remaining 40% represented retail supply chains. This balance allows for comparative insights across sectors, particularly in understanding how AI adoption, data dependency, and data quality influence forecasting accuracy in different operational contexts.

4.2 Reliability and Validity of Constructs

Construct	No. of Items	Cronbach's Alpha	AVE	√AVE
Artificial Intelligence (AI)	5	0.87	0.62	0.79
Data Dependency (M1)	4	0.85	0.59	0.77
Data Quality (M2)	4	0.83	0.57	0.75
Forecasting Accuracy (DV)	5	0.88	0.64	0.80

Table 2: Reliability and Validity of Constructs

Interpretation:

Making sure the measurements are reliable and accurate is very important for good quantitative analysis. To check how well the different parts of the study work together, we used something called Cronbach's alpha. All the parts of the study scored higher than the usual standard of 0.70, which means they are reliable. Specifically, Artificial Intelligence had a score of 0.87, Data Dependency (M1) had 0.85, Data Quality (M2) had 0.83, and Forecasting Accuracy (DV) had 0.88. These high scores show that each part of the study consistently measures what it is meant to measure, which means the tools used to collect data are dependable.

To check if the different parts of the study are measuring related things, we used a method called Average Variance Extracted (AVE). All the parts had AVE scores above 0.50, which means that most of the information from the measurements comes from the main idea they are supposed to represent. We also made sure that the square root of each AVE score was higher than the scores for how much each part was related to the others. This shows that the different parts are separate and measure different aspects, which helps avoid problems where measurements might be too similar or overlapping. These results give a solid base for testing ideas using structural equation modeling.

4.3 Model Fit Indices

Fit Index	Value	Acceptable Threshold	Interpretation
Chi-square / df (χ^2/df)	2.12	< 3	Acceptable fit
Comparative Fit Index (CFI)	0.94	> 0.90	Good fit
Root Mean Square Error of Approximation (RMSEA)	0.052	< 0.08	Low approximation error
Tucker-Lewis Index (TLI)	0.92	> 0.90	Good fit

Table 3: Model Fit Indices

Interpretation:

Before looking at how different parts of the model relate to each other, it's important to check if the whole SEM model fits the data well. These fit indices show how closely the model matches what was actually observed. The results show that the model fits the data well. The chi-square to degrees of freedom ratio was 2.12, which is lower than the 3 thresholds, meaning the fit is acceptable. The Comparative Fit Index was 0.94, which is above the 0.90 minimum. The Root Mean Square Error of Approximation was 0.052, which is under the 0.08 limit, showing little error in the model's approximation. Lastly, the Tucker-Lewis Index was 0.92, meaning the model fits the data better than a simple baseline model.

Collectively, these indices confirm that the hypothesized relationships among AI, data dependency, data quality, and forecasting accuracy are appropriate and statistically sound for testing the proposed hypotheses.

Note: These indices indicate that the hypothesized SEM model fits the observed data well.

4.4 Hypothesis Testing

Hypothesis	Path / Relationship	Path Coefficient (β)	p-value	Result
H1	AI → Forecasting Accuracy	0.42	< 0.001	Supported
H2	AI → Data Dependency → Forecasting Accuracy	0.25	0.003	Supported
H3	AI → Data Quality → Forecasting Accuracy	0.31	0.002	Supported
H4	AI → Data Dependency → Data Quality → Forecasting Accuracy	0.21	0.005	Supported

Table 4: Hypothesis Testing Results

Interpretation:

The study's hypotheses were tested by examining path coefficients and their associated p-values in the SEM model.

The first hypothesis (H1) suggested that using AI would lead to better forecasting accuracy. The analysis showed a path coefficient of 0.42 with a p-value less than 0.001, which supports H1. This means AI is a major tool that helps improve predictions, decision-making, and overall accuracy in supply chain forecasting.

The second hypothesis (H2) looked at how data dependency acts as a middle factor between AI and forecasting accuracy. The path coefficient for this was 0.25, with a p-value of 0.003, showing that data dependency plays a significant role explains part of the effect of AI on forecasting accuracy. This highlights the operational mechanism through which AI delivers value: by increasing reliance on structured, timely, and continuous data, AI systems enhance forecasting performance.

The third hypothesis (H3) looked at how data quality affects the connection between AI and forecasting accuracy. The path coefficient was 0.31, and the p-value was 0.002, supporting the hypothesis. This demonstrates that the effectiveness of AI in improving forecasting accuracy is highly contingent upon the condition of data quality, emphasizing the importance of accurate, complete, and consistent information for AI-driven decision-making.

Finally, the fourth hypothesis (H4) tested the sequential mediation effect of data dependency followed by data quality on the relationship between AI and forecasting accuracy. The analysis found a path coefficient of 0.21 with a p-value of 0.005, which shows that the sequential mediation effect is real. This means that using AI first makes people rely more on data, and then having good data helps make better predictions. It shows that implementing AI in supply chains is a complicated and multi-step process.

Overall, the results show that both the direct and indirect ways AI affects forecasting accuracy are important. Relying on data and having high-quality data work together in a certain order, which supports the theory based on Conservation of Resources (COR). These findings demonstrate that organizations adopting AI must also ensure strong data infrastructure and quality management to maximize the predictive and operational benefits of AI in supply chain forecasting.

Note: Both direct and indirect effects of AI on forecasting accuracy are significant. Data dependency and data quality act as important mediators in the model.

Chapter 5

Hypothesis Development and Discussion

5.1 Discussion

This study looked at how using Artificial Intelligence (AI) affects the accuracy of forecasting in supply chain activities. It focused on how much data is needed and how good the data quality is, as they play a key role in this process. Based on the Conservation of Resources (COR) theory, the research suggested that AI is a major resource for an organization, and its effect on forecasting results depends on having enough and high-quality data. The study used data from 384 professionals in the manufacturing and retail sectors of Pakistan. They applied strict statistical methods to examine the direct, indirect, and step-by-step connections between the different factors involved.

The findings reveal several critical insights into how AI adoption can improve forecasting performance while also highlighting the role of interdependent resources in maximizing the benefits of technological investments. Overall, the results demonstrate that AI has a significant positive direct effect on forecasting accuracy, supporting prior research emphasizing the transformative potential of AI technologies in operational contexts (Wamba et al., 2020; Gunasekaran et al., 2017). AI helps organizations handle big amounts of complicated data, find patterns, and make predictions that are hard to do with usual methods. Because of this, using AI in supply chain management makes operations run better, lowers mistakes made by people, and makes forecast predictions more accurate.

However, the study findings underscore that AI's effectiveness is not solely determined by the technology itself. The mediating effects of data dependency and data quality highlight the critical importance of the broader organizational and operational context in which AI is implemented. Data dependency, defined as the extent to which decision-making relies on continuous, structured, and accessible data, emerged as a significant mediator between AI and forecasting accuracy. This indicates that while AI systems can make predictions, but how well they work depends a lot on the data they use. The data needs to be available and easy to use for the system to perform effectively. Organizations that fail to develop robust data infrastructure or do not ensure consistent data flows may experience suboptimal AI performance despite heavy investments in technology. This finding aligns with COR theory, which posits that resources do not operate in isolation; rather, they interact synergistically, and the utility of one resource depends on the condition of others. In the context of supply chains, AI (primary resource) produces maximal forecasting benefits only when coupled with reliable data streams (supporting resource).

Moreover, the study shows that data quality plays a key role in between other factors. Data quality means that the data is accurate, has all the necessary information, stays the same across different places, is up-to-date, and is relevant to what is needed, all of which are essential for meaningful AI-driven predictions. The empirical results demonstrate that high-quality data significantly amplifies the positive effect of AI on forecasting accuracy. This reinforces the argument that even advanced AI algorithms cannot compensate for poor-quality data, which can introduce biases, errors, and flawed predictions. For example, missing inventory records, inconsistent sales data, or outdated supplier information can distort AI forecasts, leading to decisions that result in overstocking, stockouts, or production inefficiencies. Therefore, the study emphasizes that organizations must prioritize data governance, validation processes, and Real-time data integration helps make the most out of AI investments.

The sequential mediation model adds more depth by showing that AI's impact on how well predictions work is stronger when you look at how data dependence and data quality work together. This happens in a step-by-step process, AI adoption first increases organizational reliance on structured and continuous data, which then places emphasis on maintaining high data quality standards to achieve accurate forecasting outcomes. This sequential mechanism highlights the dynamic and interconnected nature of resource utilization in organizations, in line with COR theory. It also reflects the practical reality in modern supply chain operations, where data volume, variety, and velocity are rapidly increasing due to digitalization, e-commerce, and global supply chain networks. Organizations that fail to manage both the dependency on data and its quality may struggle to derive actionable insights from AI tools, even if technological adoption is high.

The results of this study match what earlier research has shown, which is that simply using AI isn't enough to make operations better. For instance, studies in supply chain analytics have argued that predictive accuracy depends not only on algorithmic sophistication but also on data availability, integrity, and organizational readiness (Choi et al., 2018). By empirically validating the mediating and sequential mechanisms, this research extends these insights and provides a theoretically grounded explanation using COR theory. It illustrates that AI should be conceptualized as a resource whose value is realized only in combination with complementary resources such as data infrastructure and quality assurance systems.

Another important contribution of this study is its empirical support for the interdependent nature of technological and informational resources in organizational performance. The results suggest that managers should not treat AI as a standalone solution but rather as part of an integrated resource system that includes data management practices, IT infrastructure, and human expertise. Effective data dependency management ensures that the organization consistently collects, organizes, and processes relevant data, while robust data quality practices guarantee that the information fed into AI models is reliable and actionable. This dual focus maximizes AI's predictive potential and enhances operational decision-making in complex, dynamic supply chain environments.

From a practical standpoint, the discussion highlights several managerial implications. First, organizations should invest in both AI capabilities and data management infrastructure simultaneously. A mismatch between sophisticated AI algorithms and low-quality or inconsistent data can negate the expected benefits of technological adoption. Second, organizations need to create clear rules for managing data, use checks to make sure data is accurate as it's received, and encourage everyone to make decisions based on data so that predictions become more reliable. Third, understanding the sequential relationship between AI, data dependency, and data quality enables managers to prioritize resource allocation and focus on interventions that have the greatest impact on operational performance. For example, training staff to manage and validate data inputs, automating data collection processes, and integrating multiple data sources can create a strong foundation for AI to function effectively.

This conversation has some important ideas. Using COR theory in the area of AI and supply chain predictions shows that technology use can be seen as a problem about how resources interact, not just a simple cause and effect situation. The empirical results reinforce the notion that resource value is contingent, interdependent, and context-sensitive. Furthermore, the study provides evidence that sequential mediation models can offer deeper insights into complex organizational processes, showing how multiple interrelated factors combine to determine outcomes. This expands the theoretical understanding of AI adoption beyond a purely technical perspective to include organizational and informational resource management considerations.

Additionally, the findings encourage a more nuanced understanding of organizational readiness for AI implementation. The emphasis on data dependency and quality suggests that firms must develop capabilities not only in AI algorithms but also in supporting processes, infrastructure, and employee competencies. Organizations that invest in building these complementary capabilities are likely to experience a higher return on AI investments, enhanced forecasting accuracy, and improved supply chain performance. This aligns with broader research in strategic management and operations, which posits that resource complementarities are essential for achieving competitive advantage.

In summary, the discussion illustrates that AI adoption in supply chain operations has significant positive effects on forecasting accuracy. However, these effects are contingent upon two critical supporting factors: data dependency and data quality. The sequential mediation model shows how these factors are connected, giving both theory and practical ideas about managing AI resources. The results add to the knowledge in AI, supply chain management, and resource-based theories, and also give managers clear advice on how to better use technology and improve business results.

This part also prepares the way for the next sections of the chapter, like summarizing the hypotheses, explaining what the findings mean for theory and practice, pointing out the study's limits, suggesting where future research could go, and wrapping up the chapter. By combining the statistical results with theoretical thinking, this section helps build a clear understanding of the complex ways AI adoption works and how it affects the accuracy of supply chain forecasts.

5.2 Summary of Hypotheses

5.2.1 Hypothesis (H1): AI - Forecasting Accuracy

Hypothesis Statement: Artificial Intelligence positively influences forecasting accuracy in supply chain operations.

Results: The hypothesis was supported – $\beta = 0.42$, $p < 0.001$

The findings show there is a strong and positive link between using AI and how accurate the forecasts. This backs up the idea that companies using AI tools can handle big amounts of structured and unstructured data, spot patterns, and make reliable predictions almost in real time. The automation and analytical capability provided by AI reduces human errors and enhances responsiveness to market fluctuations.

These results align with previous studies suggesting that AI-driven systems improve predictive capabilities in supply chains, including demand forecasting, route optimization, and inventory management (Wamba et al., 2020). From a theoretical perspective, COR theory explains that AI functions as a valuable organizational resource. Its effectiveness, however, depends on integration with other supporting resources such as data quality and data management systems. Organizations adopting AI strategically can therefore achieve improved operational efficiency and accuracy in forecasts.

5.2.2 Hypothesis (H2): Mediation - Data Dependency

Hypothesis Statement: Data dependency mediates the relationship between AI and forecasting accuracy.

Results: The hypothesis was supported – $\beta = 0.25$, $p = 0.003$

The data confirmed that AI increases reliance on continuous, structured, and timely data. This dependence, in turn, affects the accuracy of forecasting. While AI provides predictive power, the system works well only when the input data is good and stays the same every time. In line with COR theory, the reliance on data represents a critical supporting resource. Insufficient or inconsistent data flows reduce the capacity of AI systems to deliver accurate predictions, underscoring the mediating role of data dependency.

This finding is consistent with prior literature emphasizing that AI systems are highly data-dependent, and operational success is contingent upon well-established data pipelines, integrated platforms, and real-time data accessibility (Gunasekaran et al., 2017).

5.2.3 Hypothesis (H3): Mediation – Data Quality

Hypothesis Statement: Data quality mediates the relationship between AI and forecasting accuracy.

Results: The hypothesis was supported – $\beta = 0.31$, $p = 0.002$

The findings indicate that high-quality data significantly enhances the predictive performance of AI systems. Accurate, complete, timely, and relevant data inputs allow AI models to generate reliable forecasts. Conversely, poor-quality data introduces biases and errors that undermine forecasting accuracy.

From the perspective of COR theory, data quality represents a supporting resource critical for maximizing the benefits of AI as a primary resource. Organizations that invest in data governance, validation, cleansing processes help make the most out of AI's ability to improve how well operations run. These findings support earlier research that shows how important clean data is for making good decisions with AI.

5.2.4 Hypothesis (H4): Sequential Mediation – Data Dependency and Data Quality

Hypothesis Statement: Data dependency and data quality sequentially mediate the relationship between AI and forecasting accuracy.

Results: The hypothesis was supported – $\beta = 0.21$, $p = 0.005$

The results suggest a sequential mechanism where AI adoption first increases data dependency, which subsequently emphasizes the importance of data quality for achieving accurate forecasting outcomes. This sequential mediation demonstrates that AI’s impact is not merely direct; it is amplified when both data dependency and high-quality data are present.

This finding aligns closely with COR theory, which emphasizes that resource interactions, rather than single resources, determine performance outcomes. AI can only deliver its full potential when the operational infrastructure (data dependency) is matched with the condition of supporting resources (data quality). These results highlight the interconnected nature of technological adoption and resource management in modern supply chain practices.

5.3 Conclusion

This study looked at how Artificial Intelligence affects the accuracy of predictions in Pakistan's supply chain industry, considering data dependency and data quality as sequential mediators. The research was conducted using a quantitative, cross-sectional approach, gathering 384 responses from professionals in manufacturing and retail supply chains. The findings reveal significant insights into how AI adoption interacts with organizational data practices to influence operational performance.

The results show that AI alone does not guarantee improved forecasting accuracy. While AI provides advanced computational power, predictive modeling capabilities, and decision-making support, its effectiveness is heavily reliant on two critical factors: the degree to which organizations depend on data (data dependency) and the quality of the data they utilize. This demonstrates that technological adoption cannot be viewed in isolation; operational resources, processes, and organizational capabilities play an essential role in determining outcomes.

The study highlights that data dependency serves as an initial mechanism through which AI exerts influence on forecasting accuracy. Organizations that adopt AI increasingly rely on data to drive insights and predictions. However, without robust management systems and controls, increased data reliance can become a source of inefficiency or errors. Thus, organizations must develop mechanisms to ensure proper collection, storage, and accessibility of data. This matches the ideas from the Conservation of Resources (COR) theory, which focuses on how having resources is important, management, and quality of resources determine the effectiveness of interventions and innovations. AI functions as a resource, but without complementary resources such as structured data and quality control, the anticipated performance benefits may not materialize.

The second important thing, data quality, was found to have a big impact on how well AI predictions work. High-quality data ensures that AI algorithms and predictive models function accurately, minimizing errors and improving reliability. Poor data quality, on the other hand, compromises AI’s predictive capabilities, leading to inaccurate forecasts and potentially costly operational decisions. This finding underscores the importance of data governance frameworks, automated validation systems, and continuous monitoring of data integrity within supply chain organizations. It also challenges the common assumption in prior literature that AI adoption inherently leads to better outcomes; This research shows that improvements in performance depend on how good the data is.

Moreover, the study found that both data dependency and data quality together play a role in how much AI affects the accuracy of predictions, and this happens step by step. This sequential mediation highlights an interdependent process: AI increases organizational reliance on data, which in turn heightens the necessity for high-quality inputs. Only when both conditions are satisfied does AI lead to improved forecasting outcomes. From a managerial perspective, this implies that investments in AI technology alone are insufficient; organizations must simultaneously invest in employee training, data infrastructure, and quality assurance mechanisms to maximize performance.

The findings also help in understanding the bigger picture of how AI plays a strategic role in managing supply chains. Using AI shouldn't just be seen as a simple technology upgrade, but rather a component of a larger resource system that includes human expertise, organizational processes, and data management capabilities. Firms that integrate AI with robust data practices are likely to achieve operational resilience, improved decision-making, and enhanced forecasting accuracy, which ultimately can translate into cost savings, better inventory management, and higher customer satisfaction.

Additionally, the research provides important theoretical contributions by extending COR theory into the technological domain. By demonstrating that resource conditions (data dependency and quality) influence the effectiveness of AI as a resource, the study emphasizes the conditional nature of technological benefits. This extension provides a framework for future research to examine other conditional resources, such as employee skills, digital readiness, or organizational culture, in relation to technology adoption.

Finally, the study offers practical guidance for supply chain managers. AI implementation should be strategically aligned with operational and data processes. Investments in AI tools should be paired with organized methods to make sure the data these tools use is correct, uniform, and up to date. Programs to train people, shared databases, automatic checks for accuracy, and frequent reviews of data quality are important for getting the most out of AI. Policymakers and organizational leaders should also consider promoting standards for AI adoption and data management within the supply chain industry to encourage consistent and reliable implementation practices.

In summary, this research demonstrates that AI can enhance forecasting accuracy, but only within a structured and well-managed data environment. The sequential interplay between AI, data dependency, and data quality serves as a blueprint for organizations seeking to leverage technological resources effectively. This study gives real examples showing how important data is for making predictions with AI, and it also gives useful advice to managers and decision-makers on how to best use technology.

5.4 Recommendations

1. **Integrated AI and Data Strategy:** Organizations should adopt a holistic approach where AI implementation is paired with structured data governance, quality assurance, and continuous monitoring.
2. **Training and Capacity Building:** Employees must be trained on data management principles, AI usage, and forecasting analytics to ensure the effective use of technological tools.
3. **Investment in Data Quality:** Organizations should implement automated data validation, centralized databases, and routine audits to maintain high-quality inputs for AI systems.
4. **Sequential Resource Planning:** Managers should recognize the sequential relationship between AI adoption, data dependency, and data quality to allocate resources effectively and prioritize interventions.
5. **Cross-functional Collaboration:** Technology, operations, and data management teams must collaborate to ensure AI adoption translates into tangible forecasting improvements.
6. **Policy Support:** Industry regulators and policymakers should promote standards for AI adoption and data management, encouraging firms to adopt best practices for technology-enabled forecasting.

5.5 Limitations of Study

Even though this research gave some helpful information, there are some things we need to be aware first, the study was done using a cross-sectional approach, which means we can't really say for sure that AI, data dependency, data quality, and forecasting accuracy are directly connected. If we did a study over a longer period, we could better understand how these things change and relate to each other over time. Second, all the data came from just one person who works in a supply chain, which could lead to some biases in the results. If we included data from different people like managers, IT experts, or outside partners, the study would be more accurate and reliable. Third, the study only looked at companies in Islamabad, so the results might not apply well to other areas with different technology setups or business practices. Also, the research only looked at two middle factors data dependency and data quality while there might be other important factors like learning within the company, how ready they are for digital changes, or how engaged their employees are. Taking these into account in future studies could give a better picture of how AI influences forecasting accuracy. Finally, the study primarily focused on manufacturing and retail supply chains, which limits its applicability to other sectors. The dynamics and technological adoption processes in service industries, logistics, or healthcare supply chains, for example, may differ significantly. Recognizing these limitations provides a roadmap for refining future research and ensuring that findings are more generalizable and contextually robust.

5.6 Future Research Directions

Based on what was found and the study's limitations, there are several areas that could be explored in future research. First, longitudinal studies could provide deeper insights into the causal and temporal relationships between AI adoption, data dependency, data quality, and forecasting accuracy. Tracking changes over time would allow researchers to examine how improvements in AI and data management practices influence forecasting outcomes across different stages of technological implementation. Another idea is that future studies could look into more factors that might influence or change how AI affects supply chain performance, which would give a better picture of its overall impact. Variables such as organizational learning, digital readiness, employee engagement, leadership support, and technological infrastructure may play critical roles in strengthening or weakening these relationships. Third, expanding the geographic scope to include other cities, provinces, or even international contexts would improve the generalizability of the findings and reveal potential cultural or regional differences in AI adoption and data management practices. Fourth, researchers could investigate industry-specific applications of AI in diverse sectors beyond manufacturing and retail, such as logistics, healthcare, or e-commerce, to understand sectoral variations in forecasting improvement. Additionally, future studies might consider examining the interplay between AI and emerging technologies, using technologies like blockchain, the Internet of Things (IoT), and predictive analytics, we can look at how these combined tools help improve decision-making and make operations more efficient. Finally, qualitative or mixed-methods approaches could complement quantitative research by providing rich insights into organizational strategies, employee perceptions, and practical challenges associated with AI and data management, offering a holistic understanding of the mechanisms driving forecasting accuracy in supply chains.

5.7 Theoretical Implications

This study's results add valuable insights to existing theories, especially where artificial intelligence, data handling, and predicting supply chain needs meet. First, the study empirically supports the Conservation of Resources (COR) theory in a modern, technology-driven organizational context. While COR theory traditionally explains how individuals and organizations manage resources to mitigate stress and optimize performance, this research extends the theory to illustrate how technological resources specifically AI interact with supporting operational resources to produce organizational outcomes. In this context, AI is conceptualized as a high-value resource that enhances forecasting capabilities, but its effectiveness is contingent on complementary resources such as data dependency and data quality.

The confirmation of both direct and mediated relationships emphasizes that AI alone cannot guarantee improved forecasting accuracy. The mediating role of data dependency demonstrates that organizations must actively manage the flow and accessibility of data to harness AI's predictive power. Similarly, the mediation through data quality reinforces the idea that resources are only as effective as their condition allows; poor-quality data can undermine even the most sophisticated AI systems. This sequential mediation model provides an important theoretical nuance: it is not merely the presence of AI, but the careful orchestration of AI with operational resources that drives effective forecasting.

This study adds to the existing knowledge about how technology is adopted and how resources are combined within supply chains. Prior studies often focus on AI implementation or the technical capabilities of AI systems, but few explicitly examine how supporting resources shape AI's operational outcomes. By highlighting the joint effect of data dependency and data quality, this study encourages scholars to move beyond examining technology in isolation and consider interconnected resource networks as critical determinants of performance.

Additionally, this research extends empirical understanding of data-centric mediating mechanisms in supply chain analytics. While data is recognized as the "lifeblood" of AI systems, this study provides quantitative evidence that the mere availability of data is insufficient; the quality and management of these data streams directly influence forecasting outcomes. This insight reinforces theoretical frameworks in operations management and information systems, The study emphasizes the significance of having complementary resources, managing quality effectively, and integrating IT strategies in a thoughtful way. It also adds to the growing research that connects the use of AI with how well an organization performs. By demonstrating that forecasting accuracy is shaped not only by AI deployment but also by mediating operational factors, the research encourages the refinement of existing models of AI impact, suggesting that future theoretical models must account for both technical capabilities and resource interdependencies.

5.8 Practical Implications

From a management and day-to-day operations point of view, the results of this study give practical ideas that companies can use to better use AI in predicting supply chain needs. First and foremost, it is clear that investing in AI technology alone is insufficient. Organizations must simultaneously ensure that their data systems, infrastructure, and personnel are adequately prepared to support AI implementation.

The study emphasizes the importance of data management strategies. As more companies use AI, they need to pay attention to how they gather, keep, and handle data to avoid problems with inconsistent information, missing information, or delayed updates that can compromise forecasting outcomes. For example, integrating automated data validation tools, adopting standardized data formats, and ensuring seamless real-time data flows can substantially enhance AI performance.

Similarly, the mediating role of data quality highlights the critical need for data governance initiatives. Managers should focus on making sure the data they use is accurate, complete, relevant, consistent, and up to date. Using good quality data helps make better predictions and also reduces the chances of making wrong forecasts, mistakes, and inefficient operations. Organizations may consider conducting regular audits of data sources, training employees on proper data entry practices, and employing analytics dashboards to continuously monitor data integrity.

The sequential mediation findings also carry implications for strategic resource allocation. AI investments should be accompanied by targeted support for data infrastructure and skilled personnel. For instance, allocating budget for data engineers, AI analysts, and supply chain specialists can ensure that AI models are effectively integrated into operational decision-making. This resource alignment ensures that technology adoption does not merely become an expensive tool, but a value-generating mechanism for the organization.

Furthermore, the findings suggest that cross-functional collaboration is crucial. Successful AI adoption requires coordination between IT teams, supply chain managers, and Decision-makers should make sure that insights from AI are useful and match the goals of the organization. Embedding AI tools into decision-support systems, rather than using them as isolated analytics platforms, can enhance responsiveness to market fluctuations, improve inventory management, and reduce forecasting errors.

Lastly, the study has implications for organizational learning and capability building. Firms should view AI adoption as part of a broader digital transformation strategy rather than a standalone project. Continuous training programs, process redesign, and knowledge sharing are necessary to translate AI insights into tangible operational improvements. By fostering a data-driven culture and emphasizing the importance of both technological and operational resources, organizations can maximize the return on AI investments and achieve sustainable performance improvements.

5.9 Reflections

Reflecting on the research process, this study gave important insights into both the theory and real-world use of AI in supply chain management. Doing this research helped understand better how AI works with key resources, such as data dependency and data quality, to influence forecasting accuracy. Throughout the study, it became evident that technological implementation alone is insufficient without complementary organizational and operational resources. Personally, the process of designing the survey, collecting data from supply chain professionals, and analyzing it using quantitative methods reinforced the importance of methodological rigor and attention to detail. The experience highlighted challenges such as ensuring high response rates, maintaining data accuracy, and addressing potential biases, which are inherent in empirical research. Moreover, reflecting on the findings revealed the practical complexities managers face when integrating AI into decision-making processes, emphasizing that technology must be accompanied by effective data governance and employee training. From an academic perspective, the study enriched my understanding of the COR theory in a technological context and illustrated how theoretical frameworks can guide the analysis of contemporary business challenges. Overall, the research journey was intellectually stimulating, enhancing both my analytical skills and my appreciation for the strategic role of AI and data management in modern supply chains. It also underscored the value of critical thinking, adaptability, and perseverance in conducting comprehensive, high-quality research.

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