

# Smart Manufacturing Supply Chain through Artificial Intelligence Technologies: - An Empirical Study in the Ethiopian Context

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## Abstract

The advent of Artificial Intelligence (AI) has transformed various industries, with significant implications for manufacturing supply chain performance (SCP). This study aims to investigate the effects of AI-enabled factors on manufacturing SCP. Based on an extensive review of the literature, a conceptual framework integrating key AI-enabled factors and SCP was developed. Data were collected from 412 respondents from manufacturing industries in Ethiopia, and the hypothesized relationships in the proposed framework were empirically tested using Structural Equation Modeling (SEM). The results of confirmatory factor analysis demonstrated that the measurement and structural models satisfied the recommended model-fit criteria, with  $\chi^2/df < 5$ , CFI, GFI, and TLI  $> 0.90$ , and RMR and RMSEA  $< 0.08$ . In addition, the findings of the study revealed that [AI-Based Forecasting \(AIBF\)](#), [AI-Based Inventory and Procurement Management \(AIBI\)](#) and [AI-Based Logistics Optimization \(AIBL\)](#) had positive and significant effects on [cost performance \(CPE\)](#) and [delivery performance \(DPE\)](#); CPE and QPE; and DPE and [quality performance \(QPE\)](#) respectively. Similarly, both [AI-Based Predictive Analytics and Risk Management \(AIBP\)](#) and [AI-Based Decision Support and Automation \(AIBD\)](#) has positive and significant effects on CPE, DPE and QPE. The novelty of this study lies in developing and empirically validating an integrated model that links multiple AI-enabled factors with manufacturing SCP using SEM within the context of a developing country. The findings provide empirical evidence that AI-enabled capabilities can significantly enhance SCP and offer practical insights for manufacturing firms seeking to improve supply chain efficiency, responsiveness, and competitiveness through AI adoption.

**Keyword:** - Smart manufacturing, Artificial Intelligence, Supply chain, Ethiopian context

## 1. Introduction

In today's highly competitive and globalized market, supply chains face tremendous pressure to operate at the highest levels of accuracy, efficiency, and flexibility. Thus, in this increasingly competitive environment, supply chain enterprises have been forced to improve their efficiency, effectiveness and performance to sustain long-term growth and profitability [1]. Enhancing efficiency and effectiveness of the entire supply chain process plays a vital role in modern business management. An efficient supply chain helps to reduce cost and save time that can be allocated to other resources by streamlining the processes and actors involved in the network [2].

However, the existing traditional supply chain systems practiced in manufacturing industries are predominantly manual and reactive, making them vulnerable to inefficiencies, disruptions, and uncertainty [3]. According to Yesem [4] inadequate supplier performance, poor information flow, and lack of digital monitoring systems exacerbate this situation. Inventory inefficiencies in traditional supply

chain, including overstocking or stock outs, further exacerbate Demand variability, and create uncertainties in production and distribution planning, leading to financial losses and disrupted operations [5]. Additionally, according to Joel et al. [6], lack of real-time visibility across supply chain networks hinders decision making, making it difficult to respond promptly to disruptions such as delays or material shortages. Such inefficiencies in traditional supply chain system negatively affect cost, delivery, quality and flexibility, and overall sector competitiveness. Similarly the manufacturing sectors in developing country like Ethiopia suffers from persistent inefficiencies in their traditional supply chain system, leading to high cost, longer delivery time, customer dissatisfaction and compromised quality [7].

Thus, these challenges request innovative solutions to navigate complexities effectively. According to existing studies the integration of advanced technologies, particularly AI is offering transformative capabilities to overcome these obstacles. For example according to Gorecki et al. [8] one of the significant drivers of supply chain optimization in recent years has been the adoption of artificial intelligence (AI) and machine learning (ML). AI can be used to analyze data and make predictions about demand, optimize logistics and transportation routes, and identifies in efficiencies in the supply chain and has the potential to revolutionize various aspects of business operations [9]. Similarly, according to Ahmed and Sheikh [10] AI can revolutionize supply chain by offer predictive insights and real-time data analysis, which help organizations streamline operations, anticipate demand fluctuations, by facilitating more informed decision-making and optimize inventory levels. Moreover, AI like neural network has demonstrated strong potential in predictive analytics, risk assessment, and real time decision making across global supply chains [11].

Despite AI benefits in improving manufacturing supply chain performance, there is a lack of comprehensive conceptual models that integrate AI enabled factors including AIBF, AIBI, AIBL, AIBP, and AIBD and supply chain dimension that provide a holistic understanding of AI role in supply chain performance. Without such integration, it is difficult to determine whether AI adoption alone is responsible for improving performance. In addition there is lack of study that quantitatively tests the relationship between AI factors and supply chain variables. Most AI and supply chain management research has been conducted in developed economies, where technological infrastructure and digital transformation maturity are high.

Thus, to fill this gap, this study aims to investigate the effects of AI- enabled factors on supply chain performance in context of developing county in Ethiopia manufacturing sector. Accordingly, the study formulate and answer the below research questions

1. What is the AI enabled factors that enhance supply chain performance?
2. Which AI enabled factors most significantly affect supply chain performance?

## **2. Literature review**

### *2.1. Artificial Intelligence in Supply Chain Management*

The AI is defined as computer programs that can perform functions related to human intelligence, such as learning, prediction, solving problems and decision making. Huang and Rust [12] define AI as computer-based models that emulate certain capabilities of human intellect while dealing with business-related challenges. The use of AI in supply chain management helps to process huge amounts of data, find out weak links within processes and manage resources [13]. The use of the AI has broadened its scope in the following areas: demand forecasting, inventories, logistics, risks and visibility of the supply chain.

The current literature indicates positive correlations between the implementation of AI and the performance of operations within a supply chain. But depending on the supply chain activity analyzed, there might be different benefits observed from the use of AI. For instance, while Alma [14] highlights the general contributions of AI to increasing operational efficiency through the areas of demand predictions, logistics, and risk management, Wang and Liu [15] pay more attention to AI- and machine learning-based forecasting and inventory management. These authors find that AI-enabled forecasting leads to higher levels of forecasting accuracy and lower inventories. In other words, AI can positively influence supply chain efficiency through both general operational gains and forecasting activities. At the same time, an improvement in forecasting does not automatically mean an improvement in supply chain

performance because the latter depends on how forecasting information is used in inventory and production decisions.

The same difference is present in research into logistics and transportations. According to previous works [16], AI optimization can be used to save costs and increase the efficiency of transportation, while Kumar and Gupta [17] analyze the application of AI technologies in supply chain disruption risk prediction and management. The results have shown that AI technologies are useful for identifying risks and making better decisions about managing risks than traditional methods. Research work [18] has found the link between AI technologies and shortened lead time, more efficient real-time monitoring, and better decision making. Thus, the studies show that AI technologies can have a positive impact on supply chain performance through cost saving, better deliveries, and less disruption occurrence. However, the benefits mentioned above are associated with different performance criteria and cannot be regarded as equal. Improved risk prediction can help decrease disruptions, but its impact on cost and delivery performances will depend on the efficiency of following mitigation efforts. Predictive analytics and operational responsiveness are further research areas that support the role that AI may play in improving supply chain performance. The implementation of AI solutions has been linked to increased performance in inventory management, demand forecasting, transparency, and real-time monitoring [19]. For example, Chen and Wang [20] evaluated the application of AI in order fulfillment operations and observed order-processing time's reduction and higher customer satisfaction levels. This finding implies that AI can affect supply chain performance not only in terms of operational efficiency but also in customer-related activities. In addition, improved operational responsiveness, supply network security, and risk management are among other possible outcomes of using AI solutions in the supply chain management [21]. Yet, the findings related to particular AI solutions, like order fulfillment and forecasting, do not imply that all AI technologies produce the same performance improvement in supply chains.

The use of AI in demand forecasting and predictive risk management has been studied as well. Radhakrishnan et al. [22] explored the impact of AI-based demand forecasting systems that utilize machine learning techniques and data analysis. The authors conclude that there are certain benefits from the application of AI in predicting and managing supply chains, in particular, inventory-related results and order fulfillment. Positive effects of AI on the performance of supply chains were also found by Ofori et al. [23]. Moreover, predictive analytics based on AI could be used in order to identify potential disruptions and take preventive measures to ensure the continuity of supply chains [24]. AI could help in optimizing transport routes, predicting demand and identifying inefficiencies in order to become more responsive, reduce the lead time and costs [9]. In turn, AI-powered visibility allows for getting more information about the logistics and production process and detecting and correcting any problems [25]. Stoyanov [26] also analyzes the opportunities offered by AI integration for developing autonomous supply chains.

While such studies tend to highlight the advantages of AI, they differ in what application, mechanism, and results they refer to. Thus, some researchers concentrate on the precision of forecasts and inventory control [15, 22], some cover transportation and logistics [16], risk management [17, 24], order fulfillment for customers [20], or general supply chain performance [14, 23]. The variety of results obtained in the research indicates that it is necessary to explore the issue of the connection between AI and supply chain performance in terms of concrete capabilities of AI and certain aspects of performance. Furthermore, even if there is an example of the improvement of supply chain performance through the implementation of AI in one application area, it cannot be concluded that the same positive result will be observed in other manufacturing firms with various technological capacities, data availability, etc.

## *2.2. Supply Chain Performance and Its Measurement*

Supply chain performance relates to how effectively and efficiently the activities within the supply chain contribute towards the objectives of the organization. In an efficient supply chain, the objective would be to reduce any inefficiency in costs and time while ensuring that quality is maintained appropriately. The manufacturing supply chain could face difficulties in terms of inventory management, information flow, suppliers, lack of visibility, demand variation, and disruptions. These difficulties could impact the costs,

deliveries, and quality of the product. Supply chain performance is multidimensional; consequently, its assessment requires clearly defined and theoretically justified indicators. In this study, manufacturing SCP is operationalized through three dimensions: CPE, DPE, and QPE. CPE captures the extent to which supply chain activities control and reduce operational costs. DPE concerns the timely and reliable delivery of products or materials, while QPE reflects the ability to maintain the required quality of products and related supply chain outputs.

These dimensions form a focused basis for analyzing manufacturing supply chain results because cost, delivery, and quality are distinct but related dimensions of performance. Some AI applications might impact one dimension more than others. For example, forecasting and inventory management can influence cost, logistics management can improve the performance of delivery, and AI-based monitoring can help with quality activities. There is no doubt about such relationships, but they need to be verified empirically rather than assuming that any AI application will have an equal impact on all three dimensions. At the same time, the three dimensions are relevant in the context of the current study in Ethiopia where the author wants to examine how AI capabilities influence manufacturing supply chain performance. For Ethiopian manufacturing, examining cost, delivery, and quality provides a practical framework for assessing whether AI-related capabilities are associated with improvements in key operational outcomes. The relevance of these dimensions should be supported by empirical studies or credible sector reports documenting challenges related to supply chain costs, delivery performance, and product quality in Ethiopia. Accordingly, this study examines CPE, DPE, and QPE as distinct but related dimensions of manufacturing supply chain performance, enabling the relationships between AI-related predictors and each outcome dimension to be assessed separately.

### 3. Conceptual Framework

In this research, we seek to formulate the conceptual framework shown in Figure 1, based on the integration of AI enabled factors and supply chain performance. Our conceptual framework assumes that the exogenous variables called AI enabled factors: AIBF, AIBI, AIBL, AIBP, and AIBD impacts manufacturing supply chain performance CPE, DPE, and QPE in a positive ways, which are considered as endogenous variables.

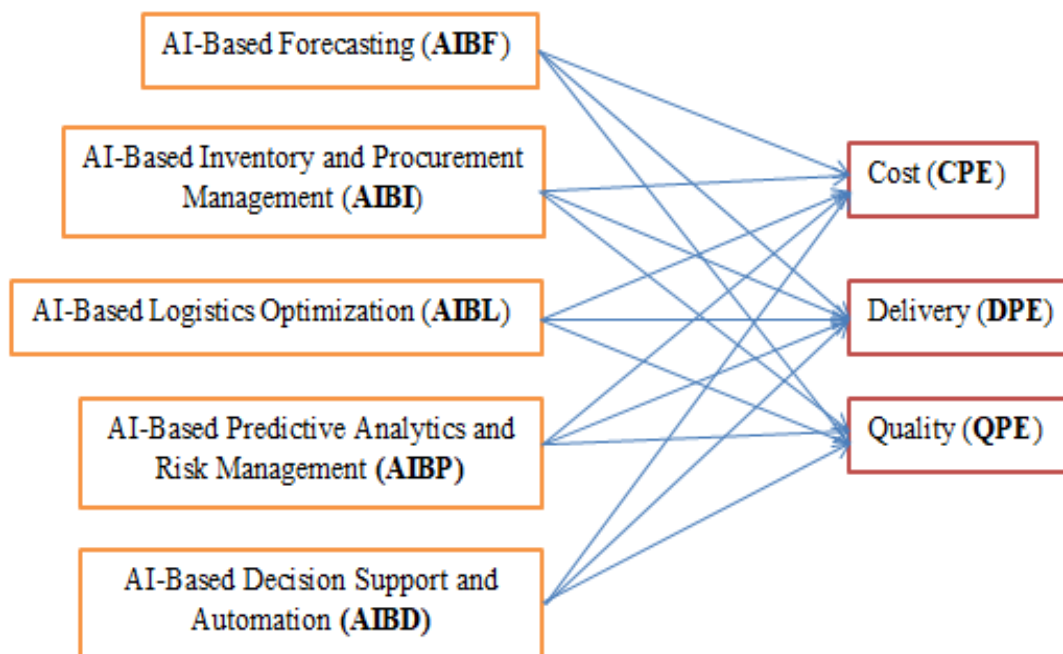


**Figure 1.** Conceptual framework of the study

#### **4. Hypotheses**

Based on reviewed literature and developed conceptual framework the following hypotheses were developed:

**Hypothesis 1(H1):-** AI based forecasting has a positive and significant effect on supply chain performance.

H1a: AI-Based forecasting has positive and significant effects on supply chain cost

H1b: AI-Based forecasting has positive and significant effects on supply chain delivery

H1c: AI-Based forecasting has positive and significant effects on supply chain quality

**Hypothesis 2 (H2):-** AI based inventory and procurement management has a positive and significant effect on supply chain performance.

H2a: AI based inventory and procurement management has positive and significant effects on supply chain cost

H2b: AI based inventory and procurement management has positive and significant effects on supply chain delivery

H2c: AI based inventory and procurement management has positive and significant effects on supply chain quality

**Hypothesis 3 (H3):-** AI based logistic optimization has a positive and significant effect on supply chain performance.

H3a: AI based logistic optimization has a positive and significant effect on supply chain cost

H3b: AI based logistic optimization has a positive and significant effect on supply chain delivery

H3c: AI based logistic optimization has a positive and significant effect on supply chain quality

**Hypothesis 4 (H4):-** AI based predictive analytics and risk management has a positive and significant effect on supply chain performance.

H4a: AI based predictive analytics and risk management has a positive and significant effect on supply chain cost

H4b: AI based predictive analytics and risk management has a positive and significant effect on supply chain delivery

H4c: AI based predictive analytics and risk management has a positive and significant effect on supply chain quality

**Hypothesis 5 (H5):-** AI based decision support and automation has a positive and significant effect on supply chain performance.

H5a: AI based decision support and automation has a positive and significant effect on supply chain cost

H5b: AI based decision support and automation has a positive and significant effect on supply chain delivery

H5c: AI based decision support and automation has a positive and significant effect on supply chain quality

#### **5. Research Methodology**

This study utilized a quantitative cross-sectional survey approach in order to investigate the effects of AI-enabled factors on supply chain performance in context of manufacturing industries in Ethiopia. A stratified random sampling technique was employed to select participants, ensuring equal representation across the selected 12 manufacturing industries in Ethiopia. A sample size of 412 was considered with 95% confidence level and a 5% margin of error, ensuring sufficient statistical power for the hypothesized regression models. Data collection was carried out using a structured 1-5 likert scale (1= strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree) questionnaire that was developed by considering literature sources that have been validated before distribution. The developed conceptual framework and hypothesis were empirically tested analyzed using SEM. The content validity was

established by conducting the experts' evaluation, whereas the construct validity was tested using Confirmatory Factor Analysis (CFA). The reliability of the variables was established through Cronbach's Alpha value above 0.70, and the convergent validity was determined using Composite Reliability (CR above 0.70) and Average Variance Extracted (AVE above 0.50). Discriminant Validity test was performed based on the Fornell-Larcker criterion [27]. Statistical analysis was conducted using SEM, where AMOS Version 25 was used to conduct the analysis in a two-step manner (measurement and structural model analysis). Model fitness was determined using conventional model fit indices (CFI, TLI, GFI  $\geq 0.90$ ; RMSEA and RMR  $\leq 0.08$ ;  $\chi^2/df = 2-5$ ) as recommended by Hair et al. [28].

## 6. Result and Discussion

### 6.1 Respondents Demographic Profile result

The demographic characteristics of the study participants (N = 412) show that 75.72 percent of the respondents were males, while females constituted 24.27 percent. With respect to age distribution, the highest proportion of respondents belonged to the age bracket of 31-40 (67.47 percent), followed by above 41 (24.75 percent) and 20-30 (7.75 percent). It suggests that the study was conducted on relatively young and professional experts. As far as education is concerned, almost more than half of the respondents had Bachelor degree (56.06 percent), while 27.18 percent had a master degree and above and only 16.74 percent possessed a diploma. It demonstrates a comparatively high educational qualification of the participants. As regards to their working experience, 60.92 percent served over ten years, 32.55 percent had 5-10 years' experience, while only 7.5 percent of the respondents have worked less than five years. Overall, the demographic profile indicates that the respondents were largely experienced and academically qualified manufacturing professionals, making them appropriate sources of information for assessing AI-enabled supply chain practices.

**Table 1.** Respondent's demographic profile

| Variable        | Category         | Frequency | Percentage (%) |
|-----------------|------------------|-----------|----------------|
| Gender          | Male             | 312       | 75.72          |
|                 | Female           | 100       | 24.27          |
| Age             | 20-30            | 32        | 7.76           |
|                 | 31-40            | 278       | 67.47          |
|                 | 41 and above     | 102       | 24.75          |
| Education Level | Diploma          | 69        | 16.74          |
|                 | Bachelor         | 231       | 56.06          |
|                 | Master and above | 112       | 27.18          |
| Experience      | <5 years         | 31        | 7.5            |
|                 | 5-10 years       | 130       | 31.55          |
|                 | >10 years        | 251       | 60.92          |

### 6.2 Reliability and Factor Loading Result

According to the analysis results presented in Table 2, the Cronbach's alpha ( $\alpha$ ) values for each construct after bad items deleted ranged from 0.806 to 0.990. This finding shows that all constructs of Cronbach's alpha ( $\alpha$ ) values are higher than the value recommended by Kline [29] as an acceptable level of 0.70. This result showed that there is strong internal consistency among all the items in each of the study's constructs. Similarly, the factor loading results in the same table shows that the items under each relevant construct have stronger connections. The entire factor load is above 0.7 (ranging from 0.796 to 0.950), which shows a strong association with the construct.

**Table 2.** Reliability analysis and factor loading result

| Constructs | Item  | Factor Loading | Cronbach's Alpha ( $\alpha$ ) |                    |
|------------|-------|----------------|-------------------------------|--------------------|
|            |       |                | Before Item Deleted           | Item After Deleted |
| AIBF       | AIBF1 | 0.884          | 0.686                         | 0.960              |
|            | AIBF2 | 0.945          |                               |                    |
|            | AIBF3 | 0.914          |                               |                    |
| AIBI       | AIBI3 | 0.923          | 0.926                         | 0.930              |
|            | AIBI4 | 0.863          |                               |                    |
|            | AIBI5 | 0.856          |                               |                    |
| AIBL       | AIBL1 | 0.920          | 0.934                         | 0.970              |
|            | AIBL2 | 0.950          |                               |                    |
|            | AIBL3 | 0.914          |                               |                    |
|            | AIBL4 | 0.939          |                               |                    |
| AIBP       | AIBP1 | 0.865          | 0.672                         | 0.933              |
|            | AIBP2 | 0.900          |                               |                    |
|            | AIBP3 | 0.888          |                               |                    |
| AIBD       | AIBD3 | 0.795          | 0.770                         | 0.806              |
|            | AIBD4 | 0.883          |                               |                    |
|            | AIBD5 | 0.918          |                               |                    |
| CPE        | CPE1  | 0.884          | 0.773                         | 0.934              |
|            | CPE2  | 0.909          |                               |                    |
|            | CPE3  | 0.921          |                               |                    |
|            | CPE4  | 0.902          |                               |                    |
| DPE        | DPE1  | 0.905          | 0.705                         | 0.930              |
|            | DPE2  | 0.880          |                               |                    |
|            | DPE3  | 0.913          |                               |                    |
|            | DPE4  | 0.892          |                               |                    |
| QPE        | QPE1  | 0.915          | 0.964                         | 0.964              |
|            | QPE2  | 0.929          |                               |                    |
|            | QPE3  | 0.950          |                               |                    |
|            | QPE4  | 0.936          |                               |                    |
|            | QPE5  | 0.935          |                               |                    |

### 6.3 Convergent and Discriminant Validity test

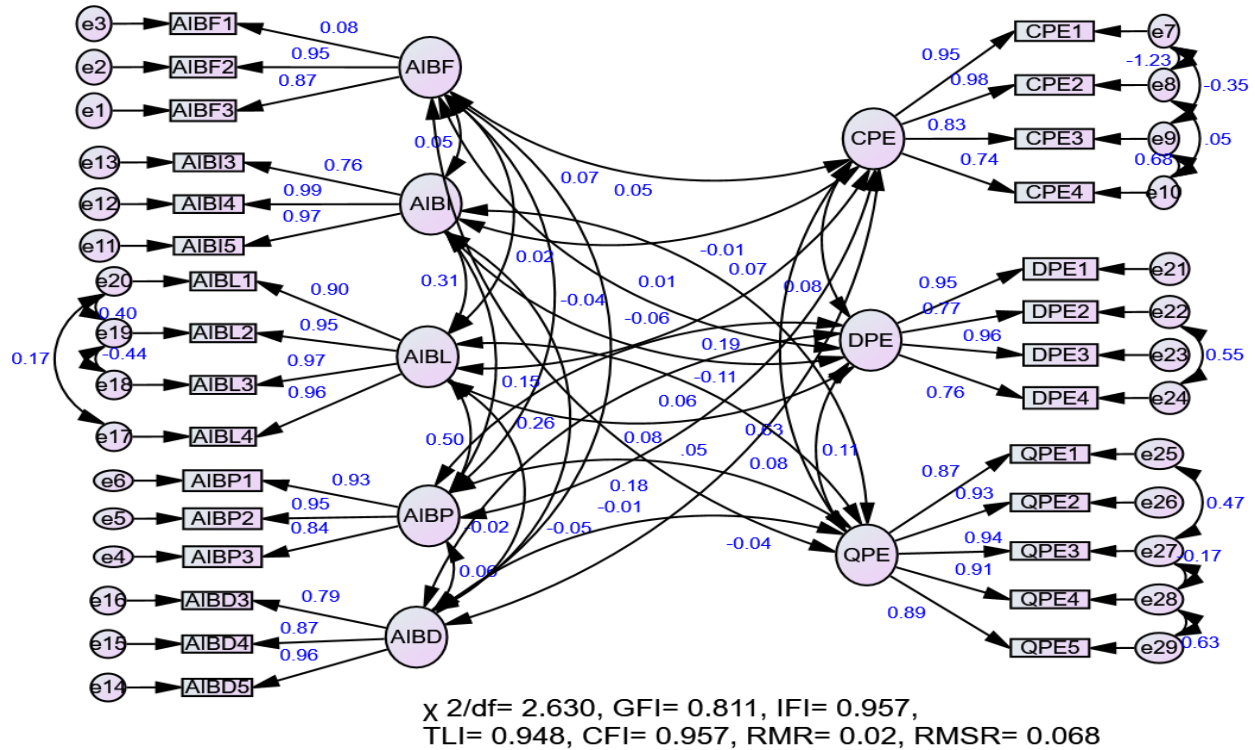
Convergent and discriminant validity tests were run following the reliability and factor loading analysis test. The findings of convergent validity test result shown in Table 3, illustrated that the values of AVE and CR for each of the constructs, respectively, surpass the cutoff limits of 0.50 and 0.70, respectively, showing that convergent validity was guaranteed [30]. In addition, the discriminant validity of the concepts used in this study is reflected in Table 3. As stated by the Fornell – Larcker criterion [27], discriminant validity is achieved when the square root of AVE in every construct is greater than the inter-constructs correlation of this construct with any other constructs. All the numbers on the diagonals (square root of AVE) of Table 3, AIBF (0.876), AIBP (0.908), AIBI (0.911), AIBL (0.994), AIBD (0.797), CPE (0.878), DPE (0.866), and QPE (0.908) are considerably higher than the off-diagonals of the same table. This shows that the construct has a higher variance compared to others since it is shared between its indicators and itself. Thus, discriminant validity is proven since constructs are unique.

**Table 3.** Convergent and Discriminant Validity test result

|      | CR    | AVE   | AIBF         | AIBP         | AIBI         | AIBL         | AIBD         | CPE          | DPE          | QPE          |
|------|-------|-------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| AIBF | 0.870 | 0.767 | <b>0.876</b> |              |              |              |              |              |              |              |
| AIBP | 0.992 | 0.835 | -.037        | <b>0.908</b> |              |              |              |              |              |              |
| AIBI | 0.993 | 0.830 | .050         | .151         | <b>0.911</b> |              |              |              |              |              |
| AIBL | 0.993 | 0.892 | .069         | .055         | .079         | <b>0.994</b> |              |              |              |              |
| AIBD | 0.989 | 0.635 | .022         | .501         | -.061        | -.024        | <b>0.797</b> |              |              |              |
| CPE  | 0.993 | 0.775 | .047         | .182         | -.006        | -.061        | .079         | <b>0.878</b> |              |              |
| DPE  | 0.987 | 0.750 | -.036        | .185         | -.113        | .079         | .262         | .081         | <b>0.866</b> |              |
| QPE  | 0.994 | 0.825 | .182         | .049         | .075         | .057         | -.006        | .027         | .109         | <b>0.908</b> |

#### 6.4 Confirmatory factor analysis

On the other hands, the measurement model test result shown in Figure 2, illustrated that the created measurement model fits well, meeting the recommended cutoff points Mia et al. [31] with the goodness of fit indices of  $\chi^2/df = 2.630$ , GFI= 0.881, IFI= 0.957, TLI= 0.948, CFI= 0.957, RMR= 0.02 and RMSR= 0.068. These confirmatory factor analysis fit indices confirmed that there is a good fit between the collected data and the created conceptual framework.

**Figure 2.** Measurement Model Test Result

#### 6.4 Structural Model Test Result

Figure 3 displays the results of the structural model's goodness of fit assessment and path analysis. The model has an excellent fit to the data, with a  $\chi^2/df$  ratio of 2.16. This is below the usual criterion of fit (less than 5), indicating a robust fit. The model fit indices also offered corroborative evidence, with RMSEA at 0.062 and RMR at 0.032, both considerably below the proposed limit of 0.08 as suggested by Brown [27]. Furthermore, the TLI = 0.938, CFI= 0.957, GFI= 0.892 and IFI= 0.946 fulfilling the

acceptance level as recommended by Brown [27]. The findings show the degree to which the structural equation model matches the empirical data, providing a solid foundation for the hypothesis' further evaluations.

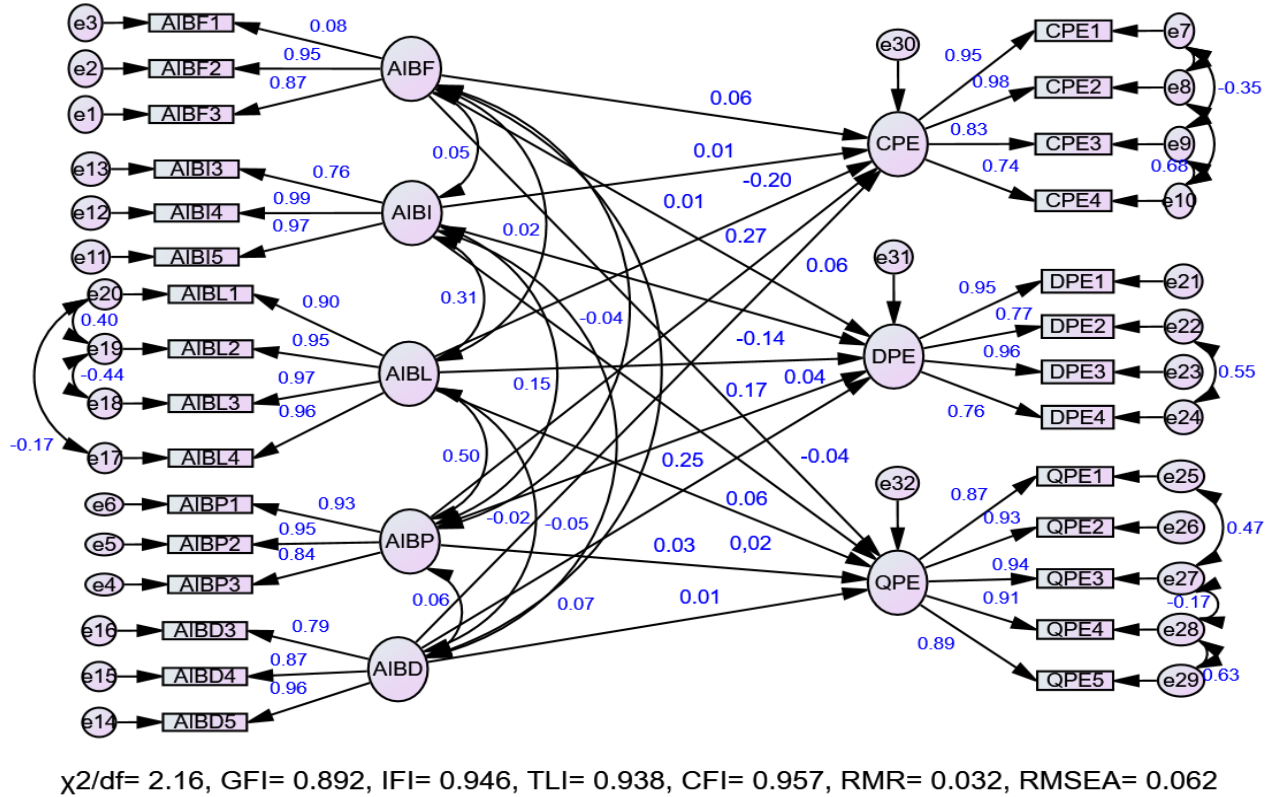


**Figure 3.** Structural model analysis result

### 6.5 Hypothesis Analysis Results

The direct effects of all the path analysis result were summarized in Table 4. According to this findings among supply chain performance measuring factors cost ( $\beta = 0.06$ ,  $p = 0.012$ ) and delivery ( $\beta = 0.01$ ,  $p = 0.000$ ) were positively and significantly affected by AI- based forecasting factors. This result supports hypothesis H1a and H1b. While hypothesis H1c is rejected with  $\beta = -0.04$  and  $p = 0.451$ . similarly AIBI factor has positive and significant effects on cost ( $\beta = 0.01$ ,  $p = 0.030$ ) and quality ( $\beta = 0.06$ ,  $p = 0.000$ ) supply chain factors. This finding supports hypothesis H2a and H2c. However, AIBI has negative and non-significant effects on delivery SCP variables. This result rejected H2b. Concerning the effects of AIBL on SCP, the findings in Table 4 revealed that delivery ( $\beta = 0.04$ ,  $p = 0.000$ ) and quality ( $\beta = 0.06$ ,  $p = 0.015$ ) SCP factors were positively and significantly affected by this AI-enabled factor. This findings supported hypothesis H3b and H3c. while, AIBL has negative and non-significant effects on CPE. This finding rejected hypothesis H3a.

On other hands, the forth sub-hypothesis (H4a, H4b, and H4c) that claims that AIBP has positive and significant effects on CPE, DPE and QPE were confirmed with ( $\beta = 0.27$ ,  $p = 0.000$ ), ( $\beta = 0.17$ ,  $p = 0.000$ ), with ( $\beta = 0.03$ ,  $p = 0.032$ ) respectively. Furthermore, AIBD factor had positive and significant effects on CPE ( $\beta = 0.06$ ,  $p = 0.000$ ), DPE ( $\beta = 0.25$ ,  $p = 0.000$ ), and QPE ( $\beta = 0.01$ ,  $p = 0.021$ ). These findings supports hypothesis H5a, H5b, and H5c.

**Table 4.** Path Analysis Result

|              | Sub-hypothesis | Paths        | $\beta$ | P     | Result   |
|--------------|----------------|--------------|---------|-------|----------|
| Hypothesis 1 | H1a            | AIBF ==→ CPE | 0.06    | 0.012 | Accepted |
|              | H1b            | AIBF ==→ DPE | 0.01    | 0.000 | Accepted |
|              | H1c            | AIBF ==→ QPE | -0.04   | 0.451 | Rejected |
| Hypothesis 2 | H2a            | AIBI ==→ CPE | 0.01    | 0.030 | Accepted |
|              | H2b            | AIBI ==→ DPE | -0.14   | 0.221 | Rejected |
|              | H2c            | AIBI ==→ QPE | 0.06    | 0.000 | Accepted |
| Hypothesis 3 | H3a            | AIBL ==→ CPE | -0.02   | 0.132 | Rejected |
|              | H3b            | AIBL ==→ DPE | 0.04    | 0.000 | Accepted |
|              | H3c            | AIBL ==→ QPE | 0.06    | 0.015 | Accepted |
| Hypothesis 4 | H4a            | AIBP ==→ CPE | 0.27    | 0.000 | Accepted |
|              | H4b            | AIBP ==→ DPE | 0.17    | 0.000 | Accepted |
|              | H4c            | AIBP ==→ QPE | 0.03    | 0.032 | Accepted |
| Hypothesis 5 | H5a            | AIBD ==→ CPE | 0.06    | 0.000 | Accepted |
|              | H5b            | AIBD ==→ DPE | 0.25    | 0.000 | Accepted |
|              | H5c            | AIBD ==→ QPE | 0.01    | 0.021 | Accepted |

## 6.6 Explanatory Power of the Structural Model ( $R^2$ )

The explanatory power of the structural model was assessed using  $R^2$ . The five AI factors jointly explained 11.6% of the variance in CPE ( $R^2 = 0.116$ ), 32.1% in DPE ( $R^2 = 0.321$ ), and 23.0% in QPE ( $R^2 = 0.230$ ). These results indicate that the model has the greatest explanatory power for delivery performance, followed by quality performance and cost performance. However, the model leaves a substantial proportion of variance unexplained, particularly for cost performance. Therefore, the findings suggest that AI-related factors contribute to explaining supply chain performance, but other organizational, technological, and operational factors may also be important

**Table 5.** Squared Multiple Correlations of Supply Chain Performance Dimensions

| Performance dimension | $R^2$ | Variance explained |
|-----------------------|-------|--------------------|
| QPE                   | 0.230 | 23.0%              |
| DPE                   | 0.321 | 32.1%              |
| CPE                   | 0.116 | 11.6%              |

## 7. Discussion

The first hypothesis is supported by the findings of Wang and Liu [15], who reported that AI-driven forecasting significantly improved demand prediction accuracy and reduced excess inventory. Integrating AI tools into supply chains can improve demand forecasting, prevent backlogs or shortages, and increase operational responsiveness. Similarly, Dubey et al. [32] found that AI-based demand forecasting can improve real-time inventory management, optimize logistics, and reduce costs. According to Mahi [33], AI-driven inventory management addresses inefficiencies in traditional manufacturing supply chains by determining reorder points, calculating safety stock levels, and managing excess inventory. AI tools can also help reduce inventory holding and storage costs by identifying slow-moving items through the analysis of sales patterns, market trends, and product life cycles. Consistent with this literature, the present study found a positive association between AIBF and CPE ( $\beta = 0.06$ ,  $P = 0.012$ ), supporting H1a. However, the relationship between AIBF and DPE, although statistically significant ( $\beta = 0.01$ ,  $p < 0.001$ ), was very small in magnitude, indicating that statistical significance should not be interpreted as evidence of a substantial practical effect. In contrast, the relationship between AIBF and QPE was negative and statistically nonsignificant ( $\beta = -0.04$ ,  $p = 0.451$ ), leading to the rejection of H1c. This finding suggests that

the benefits of AI enabled functions for forecasting and inventory management do not necessarily translate into measurable quality improvements. In Ethiopian manufacturing firms, possible explanations include limitations in production data quality, process standardization, equipment reliability, and the integration of forecasting information with quality-control activities. These explanations are plausible contextual interpretations rather than causes established by the present study.

The third hypothesis is supported by the findings of Chen and Wang [34] and Helo and Hao [35]. AI-based logistics optimization can reduce transportation costs and improve delivery times by enhancing the ability to predict and mitigate potential supply chain disruptions. AI can help businesses save transportation time and costs by identifying efficient supply chain routes. AI-enabled real-time monitoring and logistics processes can also help firms adapt to changes in demand and other disruptions, potentially improving performance. In addition, AI-driven optimization tools can enhance supply chain efficiency by identifying cost-effective transportation routes and minimizing delivery times. AI-based risk prediction and management tools can support the identification of potential risks and the mitigation of their impacts. The present findings provide differentiated empirical support for the relationship between AIBL and supply chain performance. AIBL was positively associated with DPE ( $\beta = 0.04$ ,  $p < 0.001$ ) and QPE ( $\beta = 0.06$ ,  $p = 0.015$ ), supporting H3b and H3c, respectively. However, its relationship with CPE was negative and statistically nonsignificant ( $\beta = -0.02$ ,  $p = 0.132$ ), resulting in the rejection of H3a. Thus, the results suggest that AIBL was associated with delivery and quality performance, but the study did not establish a statistically significant relationship with cost performance. One possible explanation is that AI bases logistic optimization may initially require investments in training, system adaptation, and data preparation before any cost benefits become measurable. In the Ethiopian manufacturing context, financial constraints and limited technical capabilities could potentially delay the realization of such benefits. Nevertheless, these contextual factors were not directly tested in the model and should therefore be investigated in future research. The findings of Zhang and Li [18], who reported that AI-based logistics and production optimization can reduce lead times and improve supply chain efficiency through real-time monitoring and decision-making, provide a relevant basis for interpreting the positive delivery-related association. However, the small coefficient observed in the present study suggests that the magnitude of the relationship may differ across manufacturing contexts.

The findings of Patel and Deshmukh [36] support the potential contribution of AI-based decision support and automation to manufacturing supply chain performance. Enhancing decision-making capabilities through AI tools can improve the speed and accuracy of decisions and potentially strengthen operational performance. In addition, AI-based automation can reduce human error and processing delays, improve operational speed and accuracy, and potentially lower labor costs. The present study provides empirical support for the relationship between AIBD and all three performance dimensions. The strongest association was observed between AIBD and DPE ( $\beta = 0.25$ ,  $p < 0.001$ ), followed by CPE ( $\beta = 0.06$ ,  $p < 0.001$ ) and QPE ( $\beta = 0.01$ ,  $p = 0.021$ ). These results suggest that AI-related decision-making was more strongly associated with delivery performance than with cost or quality performance in the sampled firms. The relatively larger delivery coefficient may reflect the potential relevance of timely, data-informed decisions to production scheduling, order prioritization, and responses to supply chain disruptions. However, the very small coefficients for cost and quality indicate that the corresponding associations, although statistically significant, were limited in magnitude. In Ethiopia, the operational benefits of AI-supported decisions may depend on the availability of reliable data, employees' analytical skills, and the ability of manufacturing firms to translate AI-generated recommendations into practical operational changes. These possible explanations highlight the importance of complementary organizational capabilities when interpreting the performance implications of AI.

The findings for AIBI provide further evidence that the relationship between AI and supply chain performance differs across performance dimensions. AIBI was positively associated with CPE ( $\beta = 0.01$ ,  $p = 0.030$ ) and QPE ( $\beta = 0.06$ ,  $p < 0.001$ ), supporting H2a and H2c, respectively. However, its relationship with DPE was negative and statistically nonsignificant ( $\beta = -0.14$ ,  $p = 0.221$ ), leading to the rejection of H2b. The negative coefficient does not establish that AI integration reduces delivery performance; rather, the evidence was insufficient to establish a statistically significant relationship in the present sample. One

possible explanation is that integrating AI systems does not automatically improve delivery efficiency when production scheduling, supplier coordination, material availability, and logistics activities remain constrained. In Ethiopian manufacturing, the benefits of digital integration may depend on the extent to which AI systems are connected to the operational processes that determine delivery reliability. This interpretation extends the contextual reasoning applied to the unsupported cost-related hypothesis by recognizing that the contribution of AI may be limited when complementary operational capabilities are insufficiently developed. However, these potential constraints require direct empirical examination.

The results for AIBP were comparatively consistent across the three performance dimensions. AIBP was positively associated with CPE ( $\beta = 0.27$ ,  $p < 0.001$ ), DPE ( $\beta = 0.17$ ,  $p < 0.001$ ), and QPE ( $\beta = 0.03$ ,  $p = 0.032$ ), supporting H4a, H4b, and H4c. The largest coefficient was observed for CPE, followed by DPE, while the relationship with QPE was substantially smaller. These findings suggest that AI-related predictive analytics and risk management may be more strongly associated with cost and delivery outcomes than with quality performance. Embedding AI into operational processes may help firms identify inefficiencies, coordinate activities, and improve resource utilization. Nevertheless, the relatively small quality coefficient indicates that process-level AI capabilities alone may not be sufficient to produce substantial quality improvements. Complementary quality-control practices, reliable production equipment, and standardized manufacturing procedures may also be important. These findings therefore support a differentiated interpretation of AI-related performance rather than the assumption that all AI applications produce equivalent improvements across supply chain outcomes.

Generally, the results show that AI-enabled factors were not uniformly associated with cost, delivery, and quality performance. Although most hypothesized relationships were statistically supported, several coefficients were small, and three relationships AIBF-QPE (H1c), AIBI-DPE (H2b), and AIBL-CPE (H3a) were not statistically significant. The rejected hypotheses should not be interpreted as evidence that AI is inherently ineffective. Instead, they indicate that the expected relationships were not supported by the available data for those specific performance dimensions. In the Ethiopian manufacturing context, infrastructure readiness, access to reliable data, workforce capabilities, financial resources, and the integration of digital technologies with existing operational systems may help explain why some anticipated benefits are not consistently reflected in performance outcomes. Overall, the findings suggest that the performance implications of AI depend on the specific AI enabled factors and performance dimension under consideration, underscoring the need to align AI implementation with the operational requirements and technological readiness of manufacturing firms.

## **8. Practical and Theoretical Implication**

The findings of this study provide both practical and theoretical implications for manufacturing industries, supply chain managers, policymakers, and technology practitioners in developing country Ethiopia. Practically the manufacturing firms can use AI-supported demand forecasting to improve demand visibility, reduce uncertainty, and support timely production and distribution decisions. Second, manufacturing organizations can employ AI-enabled inventory systems to improve inventory decisions, supplier management, replenishment planning, and procurement activities. In addition practically, manufacturing sectors can use AI-based route optimization, real-time logistics monitoring, transportation planning, and intelligent scheduling to reduce delivery delays and improve supply chain responsiveness. The insignificant effect of logistics optimization on cost suggests that technological adoption alone may not immediately translate into cost reductions; firms may need to combine AI logistics applications with appropriate transportation planning, infrastructure improvement, and operational management practices. Fourth, the finding of the study highlights the importance of using AI to identify potential disruptions, anticipate production risks, and support proactive mitigation. Manufacturing firms should consequently develop predictive risk-management systems capable of monitoring operational information and providing early warnings about potential disruptions.

On the other hands, theoretically, the study contributes to the emerging literature on AI-enabled smart manufacturing supply chains by developing and empirically testing an integrated framework by integrating five AI-enabled factors with manufacturing three SCP measuring variables. The conceptual

framework therefore provides a structured explanation of how different AI capabilities contribute to CPE, DPE and QPE. The empirical results provide evidence that the relationship between AI and SCP is multidimensional rather than uniform. While several AI-enabled factors positively influence SCP, their effects differ across CPPE, DPE and QPE dimensions. This finding extends the theoretical understanding of AI-enabled SCP by demonstrating that individual AI capabilities may contribute differently to specific performance outcomes. Furthermore, the study contributes empirical evidence from a developing-country manufacturing context, where the adoption and implementation conditions of AI may differ from those in developed economies. The validated measurement and structural models provide a basis for future researchers to investigate AI-enabled supply chain transformation in similar emerging manufacturing environments. The study also demonstrates the usefulness of SEM for empirically examining the relationships between multiple AI-enabled capabilities and multidimensional supply chain performance.

## 9. Conclusion

This study aims to investigate the effects of AI-enabled factors on manufacturing SCP in the Ethiopian context. Data's have been collected from 412 respondents and used to test the developed conceptual framework and hypothesis using SEM in AMOS version 24. The study empirically examined the relationships between five AI-enabled factors and three dimensions of SCP (cost, delivery, and quality). The measurement model test result demonstrated acceptable reliability and validity, while the structural model showed an acceptable overall fit to the empirical data.

The findings of the study demonstrate that AI-enabled technologies can make an important contribution to improving manufacturing SCP. AI-based forecasting significantly improved CPE and DPE, while AIBI significantly improved CPE and QPE. Similarly, the findings of the study revealed that AI-based logistics optimization significantly improved DPE and QPE, whereas AIBP significantly improved all three performance dimensions. AI-based decision support and automation also demonstrated significant positive effects on CPE, DPE and QPE.

Overall, the findings indicate that AI adoption should not be viewed as a single technological intervention. Rather, manufacturing organizations need to develop a combination of complementary AI capabilities covering forecasting, inventory and procurement, logistics, predictive risk management, decision support, and automation. Such an integrated approach can help firms improve supply chain responsiveness, reduce operational inefficiencies, strengthen decision-making, and enhance competitiveness. Therefore the study concludes that AI-enabled capabilities represent an important pathway toward smarter and more responsive manufacturing supply chains in Ethiopia. However, the effectiveness of individual AI capabilities varies according to the specific SCP dimension being targeted. Manufacturing firms should consequently prioritize AI investments according to their strategic performance requirements while simultaneously strengthening digital infrastructure, employee competencies, data availability, and organizational readiness for AI adoption.

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