

UNVEILING THE NEXUS BETWEEN AI-BASED INVENTORY MANAGEMENT SYSTEM AND PROJECT OUTCOME: EVIDENCE FROM SMES IN DELTA STATE

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ABSTRACT

This study focused on the nexus between AI-based inventory management system and project outcome. The study examined the effect of AI-driven forecast on project completion time, assessed the effect of smart supply chain on project success, and determined the effect of decision support system on project quality. This study employed a survey research design. Primary data were obtained through a structured questionnaire. The questionnaires were distributed, and 284 were returned complete and usable. The adequacy of the sample was assessed using the Kaiser-Meyer-Olkin (KMO) measure. The research instrument underwent assessment for construct validity and reliability. Descriptive statistics were used to summarise respondents' demographic characteristics, while inferential statistics supported the testing of relationships among the study variables. Regression analysis was applied at a 5% significance level. Findings revealed that AI-based forecasting has a significant positive effect on the project completion time, and that smart supply chain has a significant positive effect on project success. Findings further revealed that decision support system has a significant positive effect on project quality. The study concluded that AI-driven forecast, smart supply chain, and decision support system all improve project outcomes among SMEs in Delta State. SME owners should adopt forecasting tools that use predictive analytics, and should invest in real-time tracking and coordination tools.

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1. INTRODUCTION

Small and medium enterprises (SMEs) often rely on inventory management to keep projects running smoothly. This makes accurate forecasting, efficient supply coordination, and sound inventory decisions important for project outcomes. In recent years, business owners have invested in artificial intelligence (AI) to manage inventory, forecast demand, and support decisions that were previously based on manual

judgment (Gupta et al., 2025). The growing use of AI-based inventory systems among SMEs has increased interest in understanding how AI-driven forecasting, smart supply chain practices, and decision support systems influence project outcomes (Javaid et al., 2025). Studies (Nabot et al., 2025; Sourav et al., 2025) have shown that AI-driven forecasting can improve project completion time. In a study, Sourav et al. (2025) found that AI-based forecasting improves resource allocation and project delivery in infrastructure projects. To buttress

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this, Nabot et al. (2025) reported that AI models can predict software delivery times and support resource planning. Liang (2025) also found that AI-driven forecasting supports cost and schedule optimization among construction SMEs. Yamuna et al. (2026) further showed that AI-based forecasting improves project time estimation. These indicate that AI-driven forecasting can help firms complete projects within planned timelines. Meanwhile, the extent to which forecasting accuracy translates into shorter completion time may differ across industries and firm size.

Smart supply chain practices are also important in determining project success. Zhang et al. (2023) posit that smart supply chain management improves operational performance in manufacturing firms. Similarly, Bhattacharya and Chatterjee (2022) observed that digital project-driven supply chains support timely delivery of project resources. Isroilov and Atabek (2025) also reported that digital supply chain practices improve project management outcomes in infrastructure and engineering projects. Lee et al. (2023) further claimed that smart supply chain adoption enhances operational performance among manufacturing firms. This may imply that firms with well-coordinated supply chains are more likely to achieve project success.

Decision support systems also shape project quality. Understanding this, Almalki (2025) opined that AI-driven decision support systems improve risk mitigation and resource allocation in agile software projects. Hamid et al. (2020) also submitted that intelligent decision support systems improve the handling of IT projects. Wang (2023) reported that AI-based decision support systems improve building project management outcomes. Bilgin et al. (2023) further showed that decision support systems support better portfolio decisions in construction companies. These studies suggest that decision support systems can guide managers toward choices that improve project quality.

Previous research has examined AI-driven forecasting, smart supply chain integration, and decision support systems in relation to project outcomes. Most of this work though was carried out in manufacturing, construction, and service firms in Asia, Europe, and other developed contexts (Almalki, 2025; Zhang et al., 2023). There is still limited empirical evidence on how these AI-based inventory management practices affect project outcomes among SMEs in Nigeria. More specifically, there is a lack of evidence on these relationships among SMEs in Delta State. This gap provides the basis for the present study, which seeks to examine the effect of AI-based inventory management systems on project outcomes among SMEs in Delta State.

The objectives of the study were to:

- i. Examine the effect of AI-driven forecast on project completion time,
- ii. Assess the effect of smart supply chain on project success, and
- iii. Determine the effect of decision support system on project quality.

2. LITERATURE REVIEW

2.1 Theoretical Support

This research is theory-driven with the support from two theories, namely Resource Based View (RBV) and the Technology Acceptance Model (TAM). According to the RBV, a company gains competitive advantage if it has resources that are valuable, scarce, inimitable and non-substitutable (Barney, 1991). AI-based inventory systems fit this description. These systems enable companies to predict customer needs, manage supply chains, and inform management decisions in a manner not possible with traditional methods. This is a view that is supported by empirical evidence. Sajja et al. (2025) showed that AI-powered demand forecasting enhances supply chain responsiveness and accuracy. Likewise, Zhang et al. (2023) demonstrated that Industry 4.0-level smart supply chain management enhances the capability of the firm. Based on these insights, it appears that adopting AI-driven inventory management strategies can serve as a strategic asset that contributes to better project results. Within the RBV framework, SMEs in Delta State that adopt AI-driven forecasting, smart supply chain tools, and decision support systems are therefore positioned to achieve better project completion time, greater project success, and higher project quality than firms that rely solely on conventional inventory practices. The Technology Acceptance Model complements this perspective by explaining the behavioural dimension of AI adoption. TAM proposes that perceived usefulness and perceived ease of use jointly determine the extent to which a technology is accepted and effectively utilised (Davis, 1989). This proposition is relevant to the present study because the benefits of AI-based inventory systems are not automatic. They depend on how managers perceive and engage with these tools. Studies within the reviewed literature illustrate this dynamic. Almalki (2025) found that AI-driven decision support systems enhance risk mitigation and resource allocation only when embedded meaningfully within agile project workflows, while Wang (2023) observed that the value of intelligent decision support in building project management is realised through active managerial application rather than mere system availability. TAM therefore accounts for variation in outcomes among firms that adopt similar AI tools. Taken together, RBV explains why AI-based inventory management systems constitute a source of competitive advantage, while TAM explains why the realisation of that advantage depends on managerial perception and use. Both theories jointly provide the framework guiding this study.

2.2 Hypotheses Development

AI-based inventory management systems shape project outcomes through forecasting accuracy, supply chain coordination, and data-driven decision-making. These systems enable firms to anticipate material requirements with precision. This precision reduces delays caused by

stockouts and misaligned procurement schedules. It shortens project completion time (Sourav et al., 2025; Yamuna et al., 2026). AI-based inventory systems also provide real-time visibility across supply chains. This visibility allows firms to coordinate the movement of materials and resources. It sustains project momentum and reduces disruptions that compromise project success (Bhattacharya & Chatterjee, 2022; Isroilov & Atabek, 2025). AI-based decision support functions further strengthen project execution. They provide managers with structured, data-informed guidance for resource allocation and risk mitigation. This guidance improves the quality of decisions made throughout the project lifecycle. It raises the quality of project deliverables (Almalki, 2025; Hamid et al., 2020). AI-based inventory management systems therefore influence project outcomes through an interconnected set of forecasting, coordination, and decision-support functions. These functions jointly determine how efficiently and effectively projects are executed. This establishes AI-based inventory management as a multidimensional construct that directly determines project completion time, project success, and project quality among SMEs in Delta State.

AI-powered forecasting involves leveraging predictive analytics and machine learning to forecast future demand, resource requirements, and project timelines. Traditional forecasting approach is sometimes based on historical averages and manual judgment. These approaches fall short of dealing with the complexity of an evolving project context. These AI models analyze a vast amount of data and uncover patterns that human planners might not detect. This feature enables companies to come up with more precise estimates of the amount of time and resources required to complete a project. AI applications in project management have been recently reviewed by Adamantiadou and Tsironis (2025), who discovered that they enhance the accuracy of planning and facilitate more realistic project scheduling. Ajibade (2025) further stated that predictive analytics can be used to improve the project management process by allowing for the identification of potential delays before they occur. The arguments indicate that AI-powered forecasting enhances a company's project planning and execution capabilities while delivering within the allocated timeframe. This is substantiated by empirical studies in various project settings.

Sourav et al. (2025) investigated AI-based forecasting in the context of BRICS infrastructure investments, concluding that AI enhances the allocation of resources and project delivery results. In software project management, AI was explored by Nabot et al. (2025) and they found that predictive models were able to improve the delivery time estimate accuracy. Among construction SMEs, using AI to support forecasting led to better cost and schedule optimization, which helped to use time on projects more efficiently (Liang, 2025). Yamuna et al. (2026) also showed that the accuracy of time estimation in projects was enhanced across engineering applications using AI-based forecasting methods. Similarly, Fouad et

al. (2025) demonstrated that AI's ability to predict raw material demand diminished material shortages delays, aiding in on-time project completion. The argument, claims and findings from these studies, across various fields including infrastructure, software, construction, and engineering, consistently indicate that AI forecasting leads to better planning accuracy and mitigates delays. Based on this body of evidence, it is believed that the same impact will be observed for SMEs in Delta State. This informs the hypothesis that:

H1: AI forecasting can significantly affect project completion time.

Smart supply chain is the management of material and resource movement along a project by real time monitoring, automation and data based coordination. Smart supply chain systems give timely information on the availability and movement of resources, in contrast to traditional supply chains, which may depend on periodic inspections and late information. This aids in recognising issues early and taking action to address them before they impact project activities. For instance, Chen (2020) discovered that intelligent monitoring systems can contribute to greater visibility and control of the production processes. In addition, Ma and Qu (2020) found that real-time monitoring of production lines using the IoT decreases disruptions in the production process. Likewise, Raffik et al. (2021) concluded that automation tools and IoT-based tracking systems help to control the supply chain and ensure inventory accuracy. These indicate that smart supply chain systems may enable companies to keep materials flowing smoothly and to minimize disruptions in the process of carrying out projects.

Smart supply chain systems also enhance the coordination of other stakeholders, project teams and suppliers who participate in the delivery of a project. Helo and Shamsuzzoha (2020) noted that blockchain-based real-time supply chains boost the reliability of project deliveries, and Bhattacharya and Chatterjee (2022) said that digital project supply chains enhance coordination among supply chain and project teams. Isroilov and Atabek (2025) also identified that using digital supply chain practices positively affects project management results on infrastructure and engineering projects. Furthermore, Wei et al. (2021) provided an explanation that SCM plays a role in the overall project management performance. Zhang et al. (2023) also demonstrated the positive effect of smart supply chain adoption on operational performance of manufacturing companies in Industry 4.0 settings. Lee et al. (2023) further revealed that smart supply chain adoption has a positive effect on the operational performance of manufacturing companies in Industry 4.0 environments. Even though these studies are in different regions, they all suggest how systems of smart supply chain helps in the management of resources, coordination and project execution. The level of success of projects can also be enhanced for SMEs in Delta State through the use of smart supply chain systems based on this evidence. This is a starting point for formulating hypothesis that:

H2: Smart supply chain has a significant effect on project success.

Decision support system is using AI assisted tools to analyse data and offer managers structured guidance to take when making decisions about the project. In traditional decision-making in project management, decisions are frequently made based on experience and intuition, which can result in varying outcomes, especially when data is complex or incomplete. The limitation could be overcome, however, through the use of decision support systems, which process vast amounts of information, and potentially provide the manager with some understanding that can facilitate decision making. Hamid et al. (2020) posits that the intelligent decision support system enhanced the effective management of IT projects. AI-based Decision Support Systems were also shown to improve risk management and resource allocation in agile software project management (Almalki, 2025). The study indicates that decision support systems can be used to better determine the risk at an earlier stage and to allocate resources more appropriately, thereby aiding in better quality project execution. This trend seems to be confirmed by evidence from other project settings. In the field of building project management, Wang (2023) found an association between an AI based intelligent decision support system and outcomes. Bilgin et al. (2023) revealed that the introduction of a decision support system improved project portfolio decisions in construction companies, indicating a possible connection between the two and a more favorable match-up between project selection and intended project outcomes. Kukar et al. (2019) also reported that the decision support system was associated with increased decision quality in agricultural and farming activities. The studies conducted in IT, software, construction and agriculture contexts provide some suggestion that decision support systems could be linked to the quality of decisions made in the context of a project, but the relationship might be different depending on context. Based on this evidence, it can be assumed that the same trend is likely to exist among SMEs in Delta State, hence the hypothesis that:

H3: Decision support system has a significant effect on project quality.

3. METHODOLOGY

3.1 Research Design

This study employed a survey research design to investigate the effect of AI-based inventory management systems on project outcomes among SMEs in Delta State, Nigeria. The research was underpinned by a positivist philosophy. This holds that organizational phenomena can be objectively observed, measured, and analysed. A hypothetico-deductive approach guided the study. The relationships drawn from existing theories and prior empirical work were subjected to testing using data gathered from SMEs in Delta State.

3.2 Sampling and Data Collection

Primary data were obtained through a structured questionnaire. It was administered to owners, managers, and project personnel across selected SMEs in Delta State. To reach respondents with varying levels of digital access, the instrument was distributed in both physical and electronic formats. The data collection exercise took the period of six months. The population targeted comprised SMEs in Delta State that had incorporated some form of AI-based inventory practice into their project operations. Because the study required informed responses on AI-based inventory practices, firms were selected using a purposive sampling technique. This allowed the researchers to focus on those meeting this criterion. The questionnaires were distributed, and 284 were returned complete and usable. The adequacy of the sample was assessed using the Kaiser-Meyer-Olkin (KMO) measure, and the result affirmed that the sample size was sufficient for the study (see Table 1). A pilot test was carried out to evaluate the clarity, relevance, and reliability of the instrument (see Table 2).

Table 1. KMO and Bartlett's Test

Test	Result
KMO Measure of Sampling Adequacy	0.719
Bartlett's Test of Sphericity – (χ^2)	655.147
Degrees of Freedom	15 (p-value < 0.01)

SPSS 25.0

A KMO value of 0.719 points to good sampling adequacy, and the significant result of Bartlett's Test of Sphericity ($\chi^2 = 655.147$, p-value < 0.01) confirms that correlations among the variables were sufficient to proceed with factor analysis.

3.3 Research Instruments

The questionnaire was structured around the core constructs of the study, namely AI-driven forecast, smart supply chain, decision support system, project completion time, project success, and project quality. 24-items measuring all constructs were adapted from instruments used in earlier studies, and responses were captured on a five-point Likert scale. The instrument subsequently underwent assessment for construct validity and reliability (see Table 2).

3.4 Data Analysis Techniques

Data gathered from the field were coded, screened, and subjected to appropriate statistical procedures. Descriptive statistics were used to summarise respondents' demographic characteristics, while inferential statistics supported the testing of relationships among the study variables. Regression analysis was applied at a 5% significance level. Before the main analysis was conducted, the dataset was checked for

completeness, missing entries, and coding errors to safeguard accuracy. The model for the study is specified as follows:

$$\begin{aligned} \text{PROJ} &= f(\text{ABIMS}) \dots\dots\dots 1 \\ \text{PCT} &= a + \beta_1 \text{AFC} + \varepsilon \dots\dots\dots 2 \\ \text{PSC} &= a + \beta_1 \text{SSC} + \varepsilon \dots\dots\dots 3 \\ \text{PQT} &= a + \beta_1 \text{DSS} + \varepsilon \dots\dots\dots 4 \end{aligned}$$

Where,

a = Constant

β_1 = regression coefficient

ε = residual or stochastic term

ABIMS = AI-based inventory management system

AFC = AI-driven forecast

SSC = Smart supply chain

DSS = Decision support system

PCT = Project completion time

PSC = Project success

PQT = Project quality

4. DATA ANALYSES AND RESULTS

Table 2 shows that factor loadings across all items ranged from 0.567 to 0.965. All loadings exceeded the 0.50 threshold. This confirms that each item contributed meaningfully to its construct.

Table 2. Validation and Reliability of Instrument

Variab les	Loading	AVE	CR	Chron(α)
AFC	0.708–0.821	0.598	0.856	0.819
SSC	0.671–0.814	0.531	0.819	0.766
DSS	0.567–0.965	0.654	0.878	0.741
PCT	0.663–0.896	0.606	0.859	0.802
PSC	0.583–0.838	0.565	0.836	0.775
PQT	0.867–0.923	0.816	0.947	0.927

Source: AMOS

The AVE values ranged from 0.531 to 0.816. All the values exceeded the 0.50 benchmark for convergent validity.

Table 3. Discriminant Validity (Using Fornell-Larcker Criterion)

	AFC	SSC	DSS	PCT	PSC	PQT
AFC	0.856					
SSC	0.125	0.819				
DSS	0.350	0.123	0.878			
PCT	0.530	0.249	0.615	0.859		
PSC	0.733	0.337	0.501	0.584	0.836	
PQT	0.402	0.240	0.233	0.259	0.558	0.947

Note: Bold diagonal values are the CR.

This shows that each construct explained more variance than error across its items. The CR values ranged from 0.819 to 0.947. All values exceeded the 0.70 cut-off. This confirms strong internal consistency among the items

measuring each construct. Cronbach's Alpha values ranged from 0.741 to 0.927. All values exceeded the 0.70 threshold considered acceptable for reliability.

Table 3 shows the discriminant validity results based on the Fornell-Larcker criterion. The bold diagonal values, which represent the reliability score for each construct, stand at 0.856 for AFC, 0.819 for SSC, 0.878 for DSS, 0.859 for PCT, 0.836 for PSC, and 0.947 for PQT. In each case, this diagonal value is higher than any of the correlations that construct has with the others in its row or column. Since this holds true across all six constructs, it suggests that each one captures more variance from its own items than it shares with the rest. On this basis, discriminant validity can be considered established for AFC, SSC, DSS, PCT, PSC, and PQT.

Table 4. Demographics of respondents

Demog- raphic Variable	Category	Frequency	Percentage (%)
Gender	Male	165	58.1
	Female	119	41.9
Age Bracket	18–28 years	14	4.9
	29–39 years	57	20.1
	40–50 years	146	51.4
	51–61 years	67	23.6
Marital Status	Single	9	3.2
	Married	216	76.1
	Widow(er)	10	3.5
	Separated	39	13.7
	Divorced	10	3.5
Education Qualificati on	OND/NCE	43	15.1
	HND	51	18.0
	Bachelor's Degree	87	30.6
	Master's Degree	53	18.7
	PhD	50	17.6
Work Experienc e	< 5 year	15	5.3
	6–11 years	75	26.4
	12–17 years	82	28.9
	18–23 years	92	32.4
	> 24 years	20	7.0
Job Position	Owners	102	35
	Project personnel	115	35.9
	Management/E xecutive	67	23.6

Source: Field survey, 2026

Table 4 shows that men made up a slightly larger share of the sample than women, at 58.1% against 41.9%. Most respondents were between 40 and 50 years old (51.4%), with a further 23.6% falling between 51 and 61 years. Younger respondents in the 18-28 bracket were the

smallest group, at just 4.9%, and this points to a sample skewed toward a more mature, experienced set of workers rather than young entrants.

Marital status followed a fairly predictable pattern, with married respondents dominating at 76.1%. Separated respondents came a distant second at 13.7%, while single, widowed, and divorced respondents each made up a small sample. Education levels were reasonably spread out, though Bachelor's degree holders stood out as the largest group at 30.6%. Master's degree and PhD holders together accounted for a little over a third of respondents (18.7% and 17.6% respectively), and OND/NCE holders made up 15.1%. This suggests the sample was not just experienced but also fairly well educated.

Respondents (32.4%) had between 18 and 23 years on the job, and 28.9% of them had 12 to 17 years. Very few respondents were either new to the workforce (5.3% with under 5 years) or veterans with more than 24 years (7.0%). In terms of job position, project personnel and owners were almost evenly represented, at 35.9% and 35.0% respectively, while management and executive staff made up the remaining 23.6%.

Table 5. Regression result on AI-driven forecast and project completion time

Variable	Coeff.	Std. Error	t-Statistic	P-value
C	0.775427	0.126134	6.147650	0.0000
AFC	0.794684	0.036216	21.94312	0.0000
R-squared	0.630649	Mean dependent var		3.313380
Adj. R-squared	0.629339	S.D. dependent var		1.392952
S.E.	0.848056	Akaike info criterion		2.515278
Sum squared resid	202.8142	Schwarz criterion		2.540975
Log likelihood	-355.1694	Hannan-Quinn criter.		2.525580
F-statistic	481.5006	Durbin-Watson stat		2.220489
Prob(F-stat)	0.000000			

The regression analysis results on the effect of AI-based forecasting on project completion time are shown in Table 5. The results indicate that the effect of AFC on PCT is positive and statistically significant ($\beta = 0.795$, $t = 21.943$, $p\text{-value} < 0.01$). This means that if the forecasting is improved due to AI, then there will be a corresponding improvement in the timing of project completion. The coefficient of determination ($R^2 = 0.631$) shows that the model used for forecasting the project completion time by AI explains 63.1% of the variation. The F-statistic of 481.501 is significant at the 1% level ($p\text{-value} < 0.01$) indicating that the regression model is suitable and is a good fit for the data. The Durban-Watson statistic is 2.220 which indicates that there is no serious autocorrelation issue in the model. Based on the result, the null hypothesis is rejected and it

was concluded that AI-based forecasting has a significant positive effect on the project completion time.

Table 6. Regression result on smart supply chain and project success

Variable	Coeff.	Std. Error	t-Statistic	Prob.
C	0.599647	0.145092	4.132883	0.0000
SSC	0.823035	0.036048	22.83193	0.0000
R-squared	0.648947	Mean dependent var		3.732394
Adjusted R-squared	0.647702	S.D. dependent var		1.339350
S.E.	0.794967	Akaike info criterion		2.385985
Sum squared resid	178.2163	Schwarz criterion		2.411682
Log likelihood	-336.8099	Hannan-Quinn criter.		2.396288
F-statistic	521.2973	Durbin-Watson stat		1.923599
Prob(F-stat)	0.000000			

Table 6 shows the results of the regression analysis on the effect of smart supply chain on project success. It indicates that SSC positively and significantly affect project success ($\beta = 0.823$, $t = 22.832$, $p\text{-value} < 0.01$). The more a firm adopts smart supply chain practices, the more likely the project will be successful.

Table 7. Regression result on decision support system and project quality

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.743709	0.126471	5.880483	0.0000
DSS	0.788744	0.033441	23.58615	0.0000
R-squared	0.663608	Mean dependent var		3.559859
Adj. R-squared	0.662415	S.D. dependent var		1.209477
S.E.	0.702732	Akaike info criterion		2.139334
Sum squared resid	139.2605	Schwarz criterion		2.165031
Log likelihood	-301.7854	Hannan-Quinn criter.		2.149636
F-statistic	556.3067	Durbin-Watson stat		1.816848
Prob(F-stat)	0.000000			

According to the R^2 value of 0.649, smart supply chain explains 64.9% of the variance of the project success variable, the rest of 35.1% is explained by other factors that are not in the model. The F-statistic 521.297 is significant at the 1% level ($p\text{-value} < 0.01$), which means

that the regression model is statistically significant. The Durbin-Watson statistic at 1.924 is not far from the value of 2 indicating no serious problem with autocorrelation. From the results, the researchers found that smart supply chain has a significant effect on project success, and as such the null hypothesis is rejected. Table 7 presents the regression result on the effect of decision support system on project quality. The coefficient for DSS is 0.789. It is significant at 1% level ($t = 23.586$, $p\text{-value} < 0.01$). This indicates that decision support system has a positive and significant effect on project quality. A unit increase in decision support system leads to a 0.789 unit increase in project quality. The R^2 value is 0.664. This means that decision support system explains about 66.4% of the variation in project quality. The F-statistic is 556.307, and it is significant at the 1% level ($p\text{-value} < 0.01$). This confirms that the overall model is a good fit for the data. The Durbin-Watson statistic is 1.817. This value is close to 2, and it suggests that there is no serious autocorrelation problem in the model. Based on these results, the null hypothesis is rejected, and it is concluded that decision support system has a significant effect on project quality.

5. DISCUSSION

Finding revealed that AI-based forecasting has a significant positive effect on the project completion time. This implies that SMEs in Delta State may improve their ability to meet project timelines by using AI-based forecasting tools in their inventory operations. This is consistent with Sourav et al. (2025), who found that AI-driven forecasting improved resource allocation and project delivery in BRICS infrastructure investment. It also agrees with Nabot et al. (2025), who reported that predictive models improved the accuracy of delivery time estimates in software project management. Similarly, it supports Liang (2025) who found that AI-driven forecasting supported cost and schedule management among construction SMEs, while Yamuna et al. (2026) reported that AI-based forecasting improved the accuracy of project time estimates. These studies suggest that AI-driven forecasting can support better project time management across different sectors. The present study extends this evidence to SMEs in the Nigerian context, particularly those operating in Delta State. The finding also supports the Resource-Based View, which argues that firms can gain an advantage from resources that are valuable and difficult for competitors to copy. In this case, the ability to use AI-driven forecasting can be viewed as a useful organizational resource because it helps firms make better estimates and plan their resources more effectively. For SMEs, which often operate with limited resources, the finding suggests that investment in AI-based forecasting may help improve their ability to complete projects within the planned time. Findings showed that smart supply chain has a significant positive effect on project success. This means that SMEs

in Delta State can improve their project outcomes by adopting real-time monitoring, automation, and digitally coordinated supply chain practices. These practices can help firms track materials, coordinate suppliers, and respond more quickly to problems than traditional supply chains that depend mainly on manual processes. This finding is consistent with Bhattacharya and Chatterjee (2022), who found that digital project-driven supply chains improve coordination between suppliers and project teams. It also agrees with Isroilov and Atabek (2025), who reported that digital supply chain practices improve project management outcomes in infrastructure and engineering projects. The finding is further supported by Zhang et al. (2023) and Lee et al. (2023), who found that smart supply chain practices can improve operational performance in manufacturing firms using Industry 4.0 technologies. Similarly, Helo and Shamsuzzoha (2020) showed that real-time and technology-based supply chains can improve the reliability of project delivery. The present study extends these findings to SMEs in Nigeria, showing that the benefits of smart supply chain practices may also apply to smaller firms operating in a developing economy. The finding also supports the Resource-Based View, which suggests that firms can improve their performance when they develop and effectively use valuable resources and capabilities. A technology-enabled and well-coordinated supply chain can provide SMEs with better control over materials, information, and supplier activities. This can reduce delays and help maintain project progress. For SMEs operating with limited resources, the finding suggests that even gradual investment in supply chain digitisation may contribute to better project outcomes.

Findings revealed that decision support system has a significant positive effect on project quality. This implies that SMEs in Delta State that rely on AI-driven decision support tools for resource allocation and risk mitigation are more likely to produce higher quality project deliverables than firms that depend mainly on managerial intuition. This finding aligns with Hamid et al. (2020), who found that an intelligent decision support system improved the effective handling of IT projects. It supports Almalki (2025), who reported that AI-driven decision support enhanced risk mitigation and resource allocation in agile software project management. The finding also corroborates Wang (2023), who showed that an AI-based intelligent decision support system improved outcomes in building project management, and it confirms the pattern observed by Bilgin et al. (2023), who found that decision support systems strengthened project portfolio decisions in construction companies. Kukar et al. (2019) also found that a decision support system improved decision quality in agricultural operations, lending further support to the consistency of this relationship across unrelated sectors. In this way, the present study extends a pattern already documented in IT, software, construction, and agricultural contexts to SMEs operating in a Nigerian setting. The result also validates the Resource-Based View, since a decision support system that supplies structured, data-informed guidance

represents a resource that competitors without similar tools cannot easily replicate, positioning adopting firms to make sounder project decisions. It also supports the TAM, given that the benefit only materialises where managers engage meaningfully with the system rather than treating it as a passive tool. This finding is relevant because it suggests that even modest investment in decision support technology can translate into measurable improvements in project quality among SMEs.

6. CONCLUSION

This study has shown that AI-based inventory management systems can influence favourable project outcomes among SMEs. Based on the empirical outcome of the study, AI-driven forecast improves project completion time. Smart supply chain can improve project success while decision support system can improve project quality. AI-based inventory practices act as strategic resources that give adopting SMEs an advantage over firms using conventional methods. The study confirms the TAM. The benefits of the tools depend on how meaningfully managers use them, not simply on their availability. It is concluded that AI-driven forecast, smart supply chain, and decision support system all improve project outcomes among SMEs in Delta State. Their adoption strengthens the ability of these firms to complete projects on time, achieve success, and deliver quality outcomes.

7. IMPLICATIONS OF THE STUDY

The study carries some practical implications. First, AI-driven forecast significantly improves project completion time. SME owners should adopt forecasting tools that use

predictive analytics. These tools can estimate material needs and project timelines. This reduces delays caused by inaccurate demand estimates and poor planning. Owners who rely on manual estimation should start with simple, low-cost forecasting tools. They can scale up to more advanced systems later.

Second, smart supply chain has a significant effect on project success. SMEs should invest in real-time tracking and coordination tools. This can include basic inventory tracking software or mobile applications. These tools provide visibility into stock levels and supplier delivery schedules. This investment does not require large-scale infrastructure. Even small improvements in supply chain visibility can help SMEs avoid disruptions. These disruptions often derail project timelines and outcomes.

Third, decision support system has a positive effect on project quality. SME managers should move beyond intuition and experience alone. They should adopt simple decision support tools. Dashboards that show resource use, risk indicators, and project progress can help. These tools support more informed decisions. This is important for SMEs that lack structured decision-making processes. For policymakers and business support agencies, the findings show a need for support. SMEs need training programmes, subsidised technology access, and digital literacy initiatives. Many SMEs may want to adopt AI-based inventory systems. They may lack the technical knowledge or capital to do so. Targeted programmes can close this gap. This can help more SMEs improve project completion time, project success, and project quality.

Finally, technology providers have a market opportunity. They can develop affordable, user-friendly AI-based inventory solutions. These solutions should fit the operational realities of SMEs in developing economies. Tools designed for limited technical infrastructure and tight budgets are more likely to succeed. Firms are more likely to adopt them than tools built mainly for large enterprises.

References

- Adamantiadou, D. S., & Tsironis, L. (2025). Leveraging artificial intelligence in project management: A systematic review of applications, challenges, and future directions. *Computers*, 14(2), 66. DOI: 10.3390/computers14020066
- Ajibade, O. M. (2025). AI enhanced project management: Leveraging predictive analytics and intelligent automation. *Int. J. Res. Publ. Rev*, 6, 6828-6844.
- Almalki, S. S. (2025). AI-driven decision support systems in agile software project management: Enhancing risk mitigation and resource allocation. *Systems*, 13(3), 208. DOI: 10.3390/systems13030208
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120. DOI: 10.1177/014920639101700108
- Bhattacharya, S., & Chatterjee, A. (2022). Digital project driven supply chains: a new paradigm. *Supply Chain Management: An International Journal*, 27(2), 283-294. DOI: 10.1108/SCM-12-2020-0641
- Bilgin, G., Dikmen, I., Birgonul, M. T., & Ozorhon, B. (2023). A decision support system for project portfolio management in construction companies. *International Journal of Information Technology & Decision Making*, 22(02), 705-735. DOI: 10.1142/S0219622022500821
- Chen, W. (2020). Intelligent manufacturing production line data monitoring system for industrial internet of things. *Computer communications*, 151, 31-41. DOI: 10.1016/j.comcom.2019.12.035
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. DOI: 10.2307/249008
- Fouad, A. M., Wefki, H., & Kouta, H. (2025). AI-driven raw material demand forecasting: Towards project management practices. *Journal of Supply Chain Management Science*, 6(1-2), 1-32. DOI: 10.59490/jscms.2025.8136

- Gupta, H., Mishra, M. V. M., Grover, N., & Chourasia, R. (2025). Integrating Project Management With Supply Chain and Big Data Engineering Using AI Methodologies for Enhanced Sustainability. In *AI-Enabled Sustainable Innovations in Education and Business* (pp. 319-352). IGI Global Scientific Publishing. DOI: 10.4018/979-8-3373-3952-8.ch014
- Hamid, M., Zeshan, F., Ahmad, A., Munawar, S., Aimeur, E., Ahmed, S., ... & Yousif, M. (2020). An intelligent decision support system for effective handling of IT projects. *Journal of Intelligent & Fuzzy Systems*, 38(3), 2635-2647. DOI: 10.3233/JIFS-179550
- Helo, P., & Shamsuzzoha, A. H. M. (2020). Real-time supply chain—A blockchain architecture for project deliveries. *Robotics and Computer-Integrated Manufacturing*, 63, 101909. DOI: 10.1016/j.rcim.2019.101909
- Isroilov, S., & Atabek, R. U. (2025). Digital supply chain and project management practices for smart infrastructure and EPC engineering projects. *Archives for Technical Sciences/Arhiv za Tehnicke Nauke*, (34), 268. DOI: 10.70102/afts.2025.1834.268
- Javaid, M. S., Chauhdary, R., Waleed, A., Ahmad, F., Zubair, M., & Tariq, O. (2025, April). AI-Powered Smart Inventory Management: Enhancing Efficiency Through Predictive Analytics and Automation. In *2025 International Conference on Emerging Technologies in Electronics, Computing, and Communication (ICETECC)* (pp. 1-6). IEEE. DOI: 10.1109/ICETECC65365.2025.11070285
- Kukar, M., Vračar, P., Košir, D., Pevec, D., & Bosnić, Z. (2019). AgroDSS: A decision support system for agriculture and farming. *Computers and Electronics in Agriculture*, 161, 260-271. DOI: 10.1016/j.compag.2018.04.001
- Lee, K. L., Wong, S. Y., Alzoubi, H. M., Al Kurdi, B., Alshurideh, M. T., & El Khatib, M. (2023). Adopting smart supply chain and smart technologies to improve operational performance in manufacturing industry. *International Journal of Engineering Business Management*, 15, 18479790231200614. DOI: 10.1177/18479790231200614
- Liang, Y. (2025). AI-Driven Project Management for Construction SMEs: A Framework for Cost and Schedule Optimization. *International Journal of Engineering Advances*, 2(2), 93-100. DOI: 10.71222/qm6ebz81
- Ma, D. B., & Qu, M. F. (2020, December). Research on on-line monitoring method of automatic production line based on industrial Internet of Things. In *2020 IEEE International Conference on Industrial Application of Artificial Intelligence (IAAI)* (pp. 492-496). IEEE. DOI: 10.1109/IAAI51705.2020.9332863
- Nabot, A., Alnaimat, F., Jebreen, I., Al-Qerem, A., & Ali, A. M. (2025, May). AI for Software Project Management: Predicting Delivery Times & Resource Allocation. In *2025 12th International Conference on Information Technology (ICIT)* (pp. 277-284). IEEE. DOI: 10.1109/ICIT64950.2025.11049089
- Raffik, R., Rakesh, D., Venkatesh, M., & Samvasan, P. (2021, October). Supply Chain Control and Inventory Tracking System using Industrial Automation Tools and IIoT. In *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)* (pp. 1-5). IEEE. DOI: 10.1109/ICAECA52838.2021.9675774
- Sajja, G. S., Addula, S. R., Meesala, M. K., & Ravipati, P. (2025, June). Optimizing inventory management through AI-driven demand forecasting for improved supply chain responsiveness and accuracy. In *AIP conference proceedings* (Vol. 3306, No. 1, p. 050003). AIP Publishing LLC. DOI: 10.1063/5.0275697
- Sourav, M. S. R., Hossain, A., Islam, M. R., Wasif, M., & Samia, S. (2025). AI-Driven forecasting in BRICS infrastructure investment: impacts on resource allocation and project delivery. *Journal of Economics, Finance and Accounting Studies*, 7(2), 117-132. DOI: 10.32996/jefas.2025.7.2.11
- Wang, J. (2023, December). Intelligent decision support system for building project management based on artificial intelligence. In *Journal of Physics: Conference Series* (Vol. 2665, No. 1, p. 012022). IOP Publishing. DOI: 10.1088/1742-6596/2665/1/012022
- Wei, X., Prybutok, V., & Sauser, B. (2021). Review of supply chain management within project management. *Project Leadership and Society*, 2, 100013. DOI: 10.1016/j.plas.2021.100013
- Yamuna, S. V., Pal, R., & Nighojkar, A. (2026). Artificial Intelligence for Intelligent Forecasting in Project Time Estimation. In *EPJ Web of Conferences* (Vol. 370, p. 01031). EDP Sciences. DOI: 10.1051/epjconf/202637001031
- Zhang, G., Yang, Y., & Yang, G. (2023). Smart supply chain management in Industry 4.0: the review, research agenda and strategies in North America. *Annals of Operations Research*, 322(2), 1075-1117. DOI: 10.1007/s10479-022-04689-1

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