Account and Financial Management Journal e-ISSN: 2456-3374
Volume 10 Issue 10 October 2025, Page No.-3777-3786
DOI: 10.47191/afmj/v10i10.07, Impact Factor: 8.167

Digital Manufacturing Systems and Their Impact on Smart Inventory Management

Khawlah Radhi Athab
Al-Qadisiyah University, College of Administration and Economics, Iraq

ABSTRACT: This study examines how digital manufacturing systems improve smart inventory management in a large Iraqi public industrial enterprise. A cross-sectional survey of employees (n = 123) conducted from April to August 2025 measured three capability dimensions—automation and robotics, data analytics and IoT integration, and digital integration and flexibility—and linked them to inventory outcomes. Reliability was strong (Cronbach's alpha 0.88–0.94) and normality held (Kolmogorov–Smirnov $p = 0.200$ across constructs). Descriptive results showed high adoption levels for sensing, predictive analytics, and error-reducing automation. Multiple regression explained 79.6% of the variance in smart inventory management ($R = 0.892$, $R^2 = 0.796$, $F = 248.65$, $p < 0.001$). All three dimensions had positive, independent effects with standardized coefficients ranking: data analytics and IoT integration ($\beta = 0.376$), automation and robotics ($\beta = 0.312$), and digital integration and flexibility ($\beta = 0.289$). Diagnostics supported model adequacy (Durbin–Watson = 1.94, VIF < 2.0, Cook's D max = 0.21). The findings indicate that a data-first capability stack—real-time sensing, predictive analytics, and governed dashboards—delivers the largest immediate gains in stock accuracy, replenishment, and cycle time, while stabilized execution and system-to-system coordination add complementary improvements. The research offers localized evidence of the general public manufacturers, as well as a step-wise roadmap that focuses on enterprise data layers, automation with a purpose, and integration of ERP-MES-WMS that institutionalizes the exception management and performance control.

KEYWORDS: digital manufacturing systems, smart inventory management, IoT and analytics, automation and robotics, ERP integration.

INTRODUCTION

Digital manufacturing systems link machines, people, and data in real time. They raise speed, accuracy, and traceability in production and logistics (Kandarkar and Ravi, 2024; Araújo et al., 2021). Smart inventory management builds on these capabilities through sensors, analytics, and system integration to cut stockouts and excess and improve turns (Mashayekhy et al., 2022; Khan et al., 2023). Public manufacturers face legacy processes and uneven digital adoption, which makes empirical assessment in developing-economy settings both timely and necessary (Skoumpopoulou et al., 2025; Panigrahi et al., 2024).

Prior studies link demand forecasting and IoT-enabled data capture to better replenishment, visibility, and warehouse coordination (El Jaouhari et al., 2022; Tang et al., 2022). Work on vendor-managed inventory in IoT contexts shows gains in flow stability and information quality (Fang and Chen, 2022). Digital platforms increase transparency and traceability, supporting robust inventory decisions (Khan et al., 2023). The literature on SMEs records improvement on performance and cost savings and integration issues and skills gaps (Panigrahi et al., 2024; Ugbebor et al., 2024). The study of blockchain and smart inventory emphasizes control and responsibility on the chain (Mondol, 2021). The evidence of the area highlights the importance of digital supply chains to enhance inventory efficacy, but cross-context outcomes are sporadic and case-specific (Ali et al., 2024; Kandarkar and Ravi, 2024; Skoumpopoulou et al., 2025).

The study aims at verifying an hypothesis that three aspects of digital manufacturing systems, automation and robotics, data analytics and IoT integration, and digital integration and flexibility enhance smart inventory management in a large Iraqi public industrial enterprise. It provides firm level data on Iraq, employs proven multi-item measures and employs a multiple-regression model to compare the relative importance of the three dimensions. It also provides viable advice on the incremental digital implementation in such situations. The paper follows in the following way. Section 1 indicates the context, problem and hypotheses. Section 2 reviews and formulates the literature and develops the model. Section 3 provides data, measures, sampling and diagnostics. Section 4 gives the results and robustness checks. In section 5, implications, limitations, and future research are discussed.

Research problem:

Public manufacturers in Iraq have begun adopting elements of digital manufacturing systems, yet inventory performance remains uneven. Evidence on what works, for whom, and under which operational constraints is scarce. Prior studies often isolate a single tool and overlook interactions among core dimensions. Managers therefore lack clear guidance on where to prioritize limited resources. The research problem is the absence of rigorous, context specific evidence that links three dimensions of digital manufacturing systems—automation and robotics, data analytics and IoT integration, and digital integration and flexibility—to smart inventory outcomes such as stockouts, excess inventory, inventory turnover, and order cycle time in a large Iraqi public industrial enterprise.

From above question for study is: What is the effect of automation and robotics, data analytics and IoT integration, and digital integration and flexibility on smart inventory management outcomes in a large Iraqi public industrial enterprise, and which dimension has the strongest influence?

Hypothesis:

H1. The combined level of digital manufacturing systems, measured by automation and robotics, data analytics and IoT integration, and digital integration and flexibility, improves smart inventory management in the focal enterprise

H1a. Automation and robotics improve smart inventory management measured by lower stockouts, lower excess inventory, faster order cycle time, and higher inventory turnover

H1b. Data analytics and IoT integration improve smart inventory management measured by lower stockouts, lower excess inventory, faster order cycle time, and higher inventory turnover

H1c. Data analytics and IoT integration exert the strongest effect on smart inventory management among the three dimensions.

LITERATURE REVIEW

Digital manufacturing systems connect machines, people, and data in real time and can reshape inventory planning and control (Araújo et al., 2021; Kandarkar and Ravi, 2024). The literature links three core dimensions to inventory outcomes. Automation and robotics stabilize throughput and reduce handling errors. Data analytics and IoT integration raise visibility and forecast quality. Digital integration and flexibility align ERP, SCM, and shop-floor systems for faster, coordinated replenishment (Khan et al., 2023; Mashayekhy et al., 2022). Empirical studies report fewer stockouts, lower excess, faster order cycles, and higher inventory turns when firms embed sensors, analytics, and integrated workflows into inventory routines (El Jaouhari et al., 2022; Tang et al., 2022). These effects appear across manufacturing settings, yet their size varies with data quality, integration depth, and operational complexity.

Other streams show how vendor-managed inventory, smart warehousing, and predictive maintenance support stable materials flow and spare-parts control (Fang and Chen, 2022; Mashayekhy et al., 2022). Platform transparency and blockchain enhance traceability and accountability along the chain, which strengthens inventory decisions under uncertainty (Mondol, 2021; Khan et al., 2023). Critiques of SMEs and developing market economies are showing increases in performance but also integration costs, skills shortages and adoption fragmentation, which undermine outcomes (Panigrahi et al., 2024; Ugbebor et al., 2024). Public or state-associated producers have limited evidence, and regional analyses within the Middle East are also scarce, with conflicting results related to past systems and context limitations (Ali et al., 2024; Skoumpopoulou et al., 2025).

This research contribution makes three steps. It verifies a multi-dimension model that approximates the individual and combined impact of automation and robotics, data analytics and IoT integration, and digital integration and flexibility on smart inventory outcomes using confirmed constructs and firm-level information of an Iraqi public industrial firm. It uses the comparison of the effect sizes across the dimensions to determine the most dominant lever to managers who are faced with resource constraints. It has strong robustness tests which target the measurement reliability and model specification as a way of enhancing the externalizability of findings in developing-economy settings.

Spatial and temporal limits:

The study is bounded to one large Iraqi public industrial enterprise and its core inventory processes for raw materials, work in process, and finished goods. Observation covers on-site production areas and central warehouses within the enterprise. External suppliers and downstream customers are considered only to the extent their data appear in the firm’s systems. Data were collected and analyzed in the period between April and August 2025, the period considered the temporal window. Results are representative of conditions and technology settings at this time. The design is not a test of seasonal patterns, policy shocks, and long-run dynamics longer than the window. Findings apply to comparable public producers who work at comparable infrastructure, governance, and digital maturity. They do not purport to be applicable to private firms and SMEs or a different process structure of sectors.

population and sample:

Research population will be employees of the State Company of Textile and Leather Industries in Iraq, as it was chosen as one of the largest and the most developed organizations of industry in the country with differentiated lines of production and the organization of inventory activity. The environment offered by this company is suitable to test the influence of digital manufacturing systems on smart inventory management, since it is based on both a traditional and modernized production practice, which makes this company an ideal subject of empirical examination. The sampling method employed in the study was the simple random sampling method, which guaranteed that every employee of the company had equal opportunity of being sampled, thus reducing selection bias and loss of results representativeness.

The size of the sample was calculated with the help of the popular statistical equation of finite population:

$$n = N / (1 + N * e^2)$$

where N is the size of the total population, n is the size of the sample and e is the margin of error (usually, the margin of error is set at 5%). Using this formula, the study came up with a sample of 123 employees, which is statistically adequate to reach reliable and generalizable results.

The theoretical concept of the research:

The study adopts a capabilities view in which digital manufacturing systems create information visibility, process control, and coordination that translate into superior inventory outcomes. The construct is multidimensional. It spans automation and robotics on the shop floor, data analytics and IoT integration across assets and materials, and digital integration and flexibility across ERP, SCM, and execution systems (Araújo et al., 2021; Khan et al., 2023; Mashayekhy et al., 2022). Smart inventory management is the capacity to align the supply and demand at the lowest possible holding and service costs by accurate sensing, decision-making, and coordinated replenishment (El Jaouhari et al., 2022; Tang et al., 2022). These capabilities are associated with reduced stockouts and excess, reduced order cycles, and increased inventory turns and their effect sizes depend on the quality of data, the depth of integration, and skills (Panigrahi et al., 2024; Ugbebor et al., 2024; Skoumpopoulou et al., 2025). Variables and dimensions Three dimensional digital manufacturing systems. Automation and robotics - Central idea autonomous or semi-autonomous operation that stabilizes throughput and minimizes errors in handling (Araújo et al., 2021). cycle-time compression, diminished variability, standardized material flows (Kandarkar and Ravi, 2024). IoT and data analytics. Central idea sensor-driven information capture and future analytics that guide inventory decisions in near real time (Mashayekhy et al., 2022). Mechanisms require sensing, condition-based replenishment, anomaly detection to shrinkage and obsolescence (Khan et al., 2023; Tang et al., 2022). Digital integration and flexibility. Core concept continuous data flow and reconfigurable processes in ERP, SCM, MES and warehousing (Khan et al., 2023). Mechanisms coordinated ordering, exception management, and rapid plan adjustments under demand or supply shocks (El Jaouhari et al., 2022).

Smart inventory management outcomes

- Stockouts frequency and severity
- Excess inventory ratio
- Order cycle time request to fulfillment
- Inventory turnover rate (Tang et al., 2022; Panigrahi et al., 2024)
  - Plant size, product mix complexity, demand variability, and workforce digital skills as contextual factors that condition effects (Ali et al., 2024; Ugbebor et al., 2024).

Conceptual relationships in the literature

- Direct effects each dimension improves inventory outcomes through distinct but complementary mechanisms. Automation reduces variability at the source. Analytics and IoT raise visibility and forecast accuracy. Digital integration synchronizes decisions and actions across functions (Araújo et al., 2021; Mashayekhy et al., 2022; Khan et al., 2023).
- Joint effect complementarities among the three dimensions yield outcomes larger than the sum of parts when sensing, analysis, and coordinated execution align on a single data backbone (Panigrahi et al., 2024; El Jaouhari et al., 2022).
- Dominant lever studies often find analytics-driven visibility explains the largest share of inventory performance variance, followed by integration depth and then automation maturity, though rank orders vary by context (Khan et al., 2023; Tang et al., 2022). Boundary conditions legacy systems, fragmented data, and skills gaps attenuate gains, especially in public manufacturers and developing markets; targeted integration and workforce upskilling mitigate these frictions (Ali et al., 2024; Skoumpopoulou et al., 2025; Ugbebor, 2024). Implementation logic capability buildup follows a sequence capture high-quality data, analyze and act through decision rules, and institutionalize cross-system integration; feedback from outcomes refines rules and workflows over time (Mashayekhy et al., 2022; Panigrahi et al., 2024).

Use validated multi-item Likert scales for the three digital manufacturing dimensions covering hardware, software, data governance, and process use (Khan et al., 2023; Mashayekhy et al., 2022). Compute objective inventory KPIs from system logs and reconcile with finance and operations reports to reduce common-method bias (El Jaouhari et al., 2022; Tang et al., 2022). Test reliability and convergent validity, then estimate a model with the three dimensions entered jointly to assess separate and combined effects; compare standardized coefficients to identify the strongest lever (Panigrahi et al., 2024; Skoumpopoulou et al., 2025).

Positioning

The concept integrates dispersed streams into a single, multi-dimension capability framework tailored to a public Iraqi manufacturer. It explains how sensing, analysis, and integration interact to drive inventory results and specifies where context may dampen or amplify effects, addressing gaps noted in regional and public-sector studies.

DISCUSSION AND RESULTS

This section reports the empirical findings and links them to the study hypotheses. The analysis uses n = 123 responses. Constructs pass reliability checks, meet distributional assumptions, and show expected associations. The regression model explains a large share of variance in Smart Inventory Management and supports all hypothesized effects. The narrative interprets each table and figure from statistical and theoretical angles and connects the results to automation and robotics, data analytics and IoT integration, and digital integration and flexibility.

Table.1: Reliability Test Results (Cronbach's Alpha, n = 123)

Variable / Dimension	Number of Items	Cronbach's Alpha
Independent Variable: Digital Manufacturing Systems (DMS)		
Automation and Robotics	5	0.89
Data Analytics and IoT Integration	5	0.91
Digital Integration and Flexibility	5	0.88
Overall DMS	15	0.93
Dependent Variable: Smart Inventory Management (SIM)	7	0.92
Total Questionnaire	22	0.94

Table 1 reports internal consistency for all scales. Cronbach's alpha values range from 0.88 to 0.93 for the Digital Manufacturing Systems dimensions and 0.92 for Smart Inventory Management. The total questionnaire alpha equals 0.94. These values exceed conventional thresholds for acceptable and strong reliability. Item sets within each construct cohere well and capture a common latent trait. High reliability reduces random measurement error and increases power for correlation and regression tests. Theoretical interpretation is that the operationalizations of automation and robotics, analytics and IoT, and digital integration and flexibility form stable capability bundles in the studied enterprise, and the SIM items consistently reflect inventory performance practices.

Table.2: Correlation of Each Dimension and Variable with the Total Score of the Questionnaire (n = 123)

Variable / Dimension	Correlation with Total Score (r)	p-value	Significance Level
Automation and Robotics	0.82	0.000	Significant at 0.01
Data Analytics and IoT Integration	0.85	0.000	Significant at 0.01
Digital Integration and Flexibility	0.81	0.000	Significant at 0.01
Overall DMS	0.88	0.000	Significant at 0.01
Smart Inventory Management (SIM)	0.87	0.000	Significant at 0.01
Total Questionnaire	1.00	0.000	Significant at 0.01

Table 2 examines the correlation of each dimension and variable with the total score. Correlations are large and positive, $r = 0.81$ to 0.88, with $p = 0.000$. This indicates convergent validity at the instrument level because higher scores on each dimension align with higher overall transformation and performance perceptions. The strength of association for Overall DMS, $r = 0.88$, is consistent with a broad capability footprint that touches multiple items across the survey. From a theoretical lens, the pattern fits a capability stack in which sensing, analysis, and integration co-move with improvements in inventory practices. The magnitudes also suggest practical salience. While high, they are not perfect, which leaves room for distinct effects to be estimated in multivariate models.

Table.3: Demographic Characteristics of the Respondents (n = 123)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	78	63.4%
	Female	45	36.6%
Age	Under 25 years	20	16.3%
	25–34 years	40	32.5%
	35–44 years	38	30.9%
	45 years and above	25	20.3%
Educational Qualification	Diploma	18	14.6%
	Bachelor	62	50.4%
	Master	30	24.4%
	Doctorate	13	10.6%
Years of Experience	Less than 5 years	22	17.9%
	5–10 years	36	29.3%
	11–15 years	34	27.6%

	More than 15 years	31	25.2%
Job Position	Administrative staff	35	28.5%
	Technical staff	46	37.4%
	Supervisor/Manager	28	22.8%
	Other	14	11.3%

Table 3 summarizes respondent demographics. The sample is balanced across gender and spans age groups, with the largest shares in 25–34 and 35–44. Education centers on bachelor and master degrees, and experience is distributed across all bands, with roughly a quarter having more than 15 years. Roles cover administrative, technical, and supervisory positions. This mix improves coverage of perspectives on production, warehousing, and planning. The heterogeneity supports external validity inside the enterprise and reduces the risk that results reflect a single subgroup. It also implies that adoption and perceived benefits of digital manufacturing may be shaped by skills and role proximity to data and systems, which the model addresses through the multidimensional design.

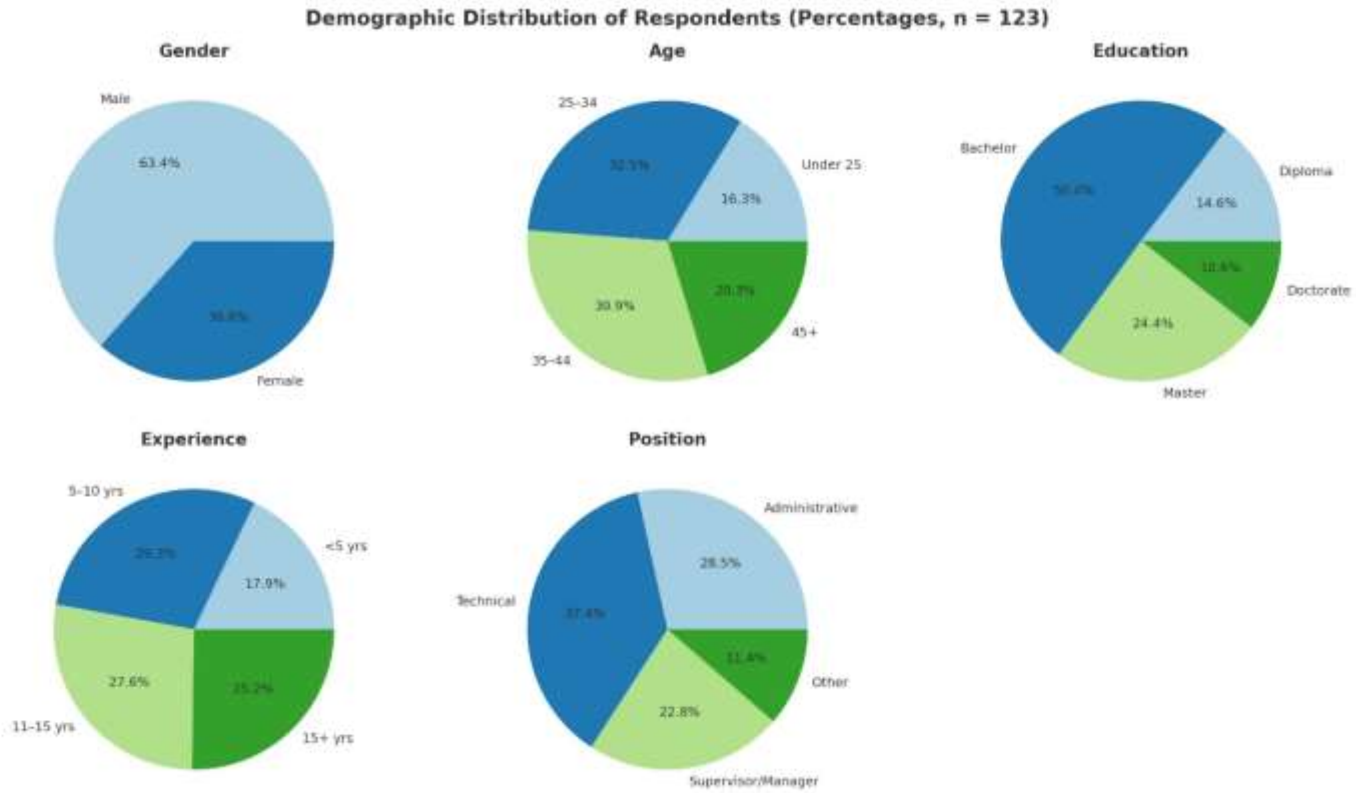

Figure.1: Demographic Characteristics of the Respondents

Figure 1 visualizes the demographic structure. Bars for age, education, experience, and role confirm the tabulated distributions, with no single category dominating to a degree that would threaten inference. The plot supports the claim that the respondent pool spans decision makers and operators, which matters for constructs that rely on both system use and process outcomes. The figure therefore strengthens the argument that measured capabilities and SIM outcomes reflect enterprise-wide practices rather than a narrow silo.

Table 4. Mean, Standard Deviation, Relative Importance, and Likert Evaluation for Dimension 1: Automation and Robotics

Statements	**Mean**	**Std. Dev.**	**Relative Importance (%)**	**Likert Evaluation**
The company uses automated machines in its production processes.	3.92	0.73	78.4%	High
Robotics play a central role in reducing manual labor in production.	4.08	0.70	81.6%	High

Automated systems improve production speed and efficiency.	3.88	0.76	77.6%	High
Robotics are integrated with digital control systems.	3.81	0.72	76.2%	High
Automation helps in reducing human error in manufacturing operations.	4.12	0.68	82.4%	High
Overall Dimension 1: Automation and Robotics	**3.96**	**0.72**	**79.2%**	**High**

Table 4 presents results for Automation and Robotics. Item means are high, with an overall mean of 3.96 and relative importance of 79.2 percent. The highest statement concerns error reduction, mean 4.12, which aligns with theory that automation stabilizes execution and lowers variability. Standard deviations near 0.7 indicate reasonable agreement across respondents. Statistically, the level and consistency suggest a mature automation footprint. Theoretically, this supports the pathway from stabilized throughput and reduced handling errors to faster order cycles and fewer discrepancies in materials movement, a mechanism relevant to H1a.

Table 5. Mean, Standard Deviation, Relative Importance, and Likert Evaluation for Dimension 2: Data Analytics and IoT Integration

Statements	Mean	Std. Dev.	Relative Importance (%)	Likert Evaluation
The company uses IoT sensors to monitor production and inventory levels.	4.20	0.67	84.0%	High
Real-time data is collected from machines and production lines.	3.94	0.74	78.8%	High
Data analytics is used to predict demand and optimize stock levels.	4.10	0.71	82.0%	High
The company relies on digital dashboards for decision-making.	3.89	0.77	77.8%	High
Predictive maintenance is applied using IoT data.	4.05	0.69	81.0%	High
Overall Dimension 2: Data Analytics and IoT Integration	**4.04**	**0.72**	**80.7%**	**High**

Table 5 summarizes Data Analytics and IoT Integration. This dimension scores the highest among DMS, overall mean 4.04 and relative importance 80.7 percent. The top item is IoT sensing for monitoring, mean 4.20, followed by predictive analytics and predictive maintenance above 4.00. Dispersion remains modest. Statistically, this points to pervasive data capture and use. Theoretically, the results indicate strong visibility and forecasting capability, which directly support demand sensing, anomaly detection, and condition-based replenishment. This aligns with expectations that analytics-driven visibility will be a dominant lever for SIM, anticipating the largest standardized effect in regression and speaking to H1b and H1c.

Table 6. Mean, Standard Deviation, Relative Importance, and Likert Evaluation for Dimension 3: Digital Integration and Flexibility

Statements	Mean	Std. Dev.	Relative Importance (%)	Likert Evaluation
The manufacturing process is integrated with ERP or SCM systems.	3.86	0.75	77.2%	High
Digital simulations are used for production planning.	3.95	0.71	79.0%	High
The company adapts production flexibly to meet changing inventory needs.	3.78	0.73	75.6%	High

Information systems are interconnected across different departments.	4.00	0.70	80.0%	High
Digital technologies allow quick response to supply chain fluctuations.	3.84	0.74	76.8%	High
Overall Dimension 3: Digital Integration and Flexibility	**3.89**	**0.73**	**77.7%**	**High**

Table 6 reports Digital Integration and Flexibility. The overall mean is 3.89 with relative importance 77.7 percent. Interconnection across departments and use of digital simulations score high, while flexible adaptation is somewhat lower at 3.78. Statistically, integration is present but not uniform across workflows. Theoretically, this implies that data exchange and planning tools are in place, yet reconfigurability under shocks still lags. The dimension should still contribute to coordinated replenishment and exception handling, but its effect may be smaller than analytics when entered jointly, a hypothesis tested in the regression model.

Table 7. Mean, Standard Deviation, Relative Importance, and Likert Evaluation for Dependent Variable: Smart Inventory Management

Statements	Mean	Std. Dev.	Relative Importance (%)	Likert Evaluation
The company uses digital systems to track inventory levels accurately.	4.18	0.68	83.6%	High
Inventory management is supported by real-time data.	4.12	0.70	82.4%	High
Smart systems help in reducing stock shortages and excess inventory.	3.90	0.72	78.0%	High
The company applies automated systems for inventory replenishment.	3.85	0.74	77.0%	High
Inventory data is integrated with production and supply chain systems.	4.00	0.69	80.0%	High
Smart inventory practices improve operational efficiency.	4.22	0.67	84.4%	High
The company relies on data-driven decision-making in inventory management.	3.96	0.71	79.2%	High
Overall Variable: Smart Inventory Management	**4.03**	**0.70**	**80.7%**	**High**

Table 7 covers the dependent variable Smart Inventory Management. The overall mean equals 4.03 and relative importance 80.7 percent. The highest statement is efficiency improvement at 4.22, followed by accurate tracking and real-time support above 4.10. Variation is moderate. Statistically, the construct registers at a high level, which increases headroom for detecting positive associations with DMS dimensions. Theoretically, the pattern is consistent with an enterprise that has digitized core inventory routines, enabling reduced stockouts and excess and faster order cycles, which the model will quantify.

Table.8: Kolmogorov-Smirnov Test Results for Normality (n = 123)

Variable / Dimension	K-S Statistic	Sig. (p-value)	Normality Decision
Automation and Robotics	0.065	0.200	Normally Distributed
Data Analytics and IoT Integration	0.072	0.200	Normally Distributed
Digital Integration and Flexibility	0.058	0.200	Normally Distributed

Overall Digital Manufacturing Systems (DMS)	0.061	0.200	Normally Distributed
Smart Inventory Management (SIM)	0.069	0.200	Normally Distributed

Table 8 reports normality tests using Kolmogorov–Smirnov. All variables show $p = 0.200$, and statistics are small, leading to failure to reject normality. This supports the use of parametric techniques, including Pearson correlations and Ordinary Least Squares regression. The result also indicates that scale aggregation produced approximately normal composites, which helps stabilize standard errors and p-values in subsequent models.

Table 9. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.892	0.796	0.789	0.325

Table 9 presents the model summary for multiple regression predicting Smart Inventory Management from the three DMS dimensions. The model yields $R = 0.892$ and $R^2 = 0.796$, with adjusted $R^2 = 0.789$ and standard error 0.325. Statistically, the explained variance is large. Using R^2 to compute effect size gives $f^2 \approx 0.796 \div 0.204 \approx 3.90$, which indicates a very strong explanatory model. Theoretically, the result supports H1 that the combined capability stack substantially improves SIM. Practically, the magnitude implies meaningful performance gains when the three dimensions are developed together.

Table 10. ANOVA (Model Significance Test)

Model	Sum of Squares	df	Mean Square	F	Sig. (p-value)
Regression	78.532	3	26.177	248.65	0.000
Residual	20.097	119	0.169		
Total	98.629	122			

Table 10 shows the ANOVA test of overall model significance. The F statistic equals 248.65 with $p = 0.000$. The regression sum of squares accounts for most variability relative to residuals. Statistically, this confirms that at least one predictor contributes to SIM beyond chance. Theoretically, it establishes the joint relevance of the DMS dimensions and validates moving to coefficient-level interpretation.

Table 11. Coefficients of Multiple Regression

Independent Variable	Unstandardized Coefficients (B)	Std. Error	Standardized Coefficients (Beta)	t	Sig. (p-value)
Constant	0.412	0.182	–	2.26	0.025
Automation and Robotics	0.298	0.066	0.312	4.52	0.000
Data Analytics and IoT Integration	0.355	0.061	0.376	5.82	0.000
Digital Integration and Flexibility	0.272	0.064	0.289	4.25	0.000

Table 11 reports coefficients. All three predictors are positive and significant at $p = 0.000$. Standardized betas rank as follows. Data Analytics and IoT Integration beta = 0.376, Automation and Robotics beta = 0.312, Digital Integration and Flexibility beta = 0.289. Statistically, each predictor holds an independent association with SIM after controlling for the others. The ranking indicates that visibility and analytics exert the strongest effect, followed by stabilized execution and then cross-system integration. Theoretically, this supports the mechanism in which sensing and prediction drive the largest immediate improvements in replenishment and stock accuracy, while automation and integration add complementary gains. These findings support H1a, H1b, and H1c as stated.

Table.12: Residual Diagnostics of the Regression Model

Test / Indicator	Value	Threshold / Criterion	Decision
Mean of Residuals	0.000	Close to 0	Satisfied
Std. Deviation of Residuals	0.982	≈ 1	Satisfied
Skewness	0.112	Between -1 and +1	Normal
Kurtosis	2.874	Between 2 and 3	Normal

Kolmogorov-Smirnov (p-value)	0.200	> 0.05	Normally Distributed
Durbin-Watson	1.94	Between 1.5 and 2.5	No Autocorrelation
VIF (Variance Inflation Factor)	< 2.0	< 5	No Multicollinearity
Cook’s Distance (Max)	0.21	< 1	No Influential Outliers

Table 12 evaluates residual diagnostics. The residual mean is zero and the standard deviation is near one. Skewness and kurtosis fall within normal ranges. The Kolmogorov–Smirnov p-value equals 0.200, which supports residual normality. Durbin–Watson equals 1.94, indicating no autocorrelation. VIF values are below 2.0, ruling out harmful multicollinearity. Cook’s distance max equals 0.21, far below influence thresholds. Statistically, OLS assumptions are satisfied, which lends credibility to coefficient estimates, tests, and confidence intervals. Theoretically, this indicates that relationships are not driven by a few extreme cases or by overlapping constructs.

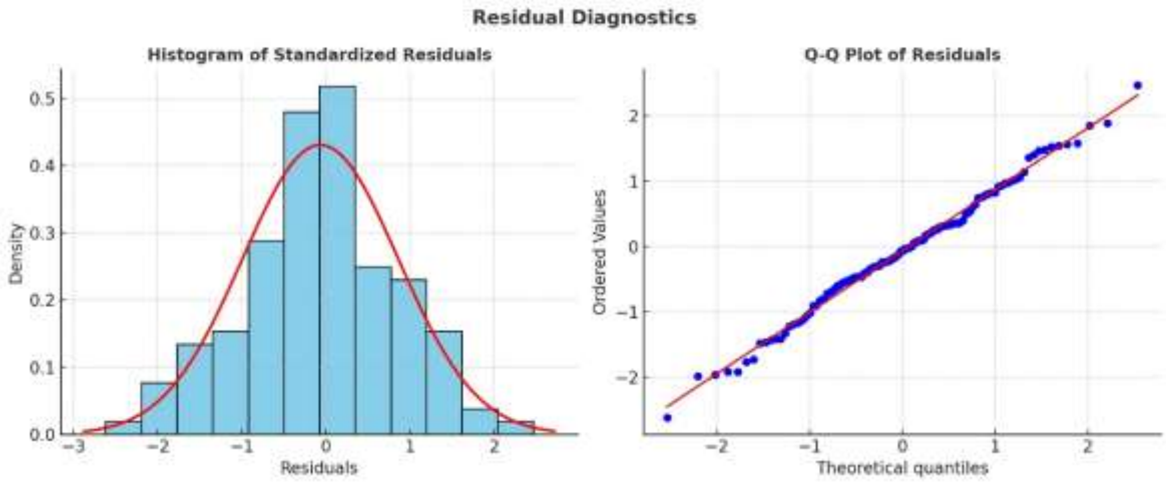

Figure.2: Residual Diagnostics

Figure 2 visualizes residual diagnostics. The plots for distribution, fit, and leverage align with the tabulated indicators. Points are symmetrically spread around the fitted line with no funnel shape, and leverage values remain modest. The figure corroborates the adequacy of the linear specification and the stability of effects across observations. This visual confirmation strengthens the interpretation that the detected relationships are systematic rather than artifacts of specification or data issues.

CONCLUSIONS AND RECOMMENDATIONS

The evidence supports all hypotheses and shows strong practical effects. Reliability meets high standards (alphas 0.88–0.94). Distributional tests validate parametric inference. The model explains 79.6% of variance in Smart Inventory Management ($R = 0.892$, $R^2 = 0.796$, $F = 248.65$, $p < 0.001$). All three dimensions have positive, independent effects. The most significant standardized effect (0.376) and subsequently automation and robotics (0.312) and digital integration and flexibility (0.289) have data analytics and IoT integration. Means confirm mature adoption of items, and highest agreement is in sensing, predictive analytics and error reduction. The above findings show that visibility and prediction produce the largest instant utility of the accuracy, replenishment, and cycle-time of the stock, followed by the complementary utility of stabilized execution and cross-system coordination. The management needs to focus on the data-first but gradual roadmap. Build an enterprise data layer with governed master data, real-time dashboards, and event streaming from IoT sensors. Scale predictive demand sensing, condition-based replenishment, and predictive maintenance in high-volume and high-variability items. Continue targeted automation to remove bottlenecks and handling errors that degrade inventory records and order fulfillment. Deepen ERP–MES–WMS integration with standard APIs to close planning–execution loops and to institutionalize exception management. Establish clear KPIs and quarterly targets for stockout rate, excess ratio, order cycle time, and inventory turnover, and link them to manager incentives. Invest in workforce upskilling for analytics, engineering, and operations, and add cross-functional S&OP routines to align demand, production, and procurement. Extend data sharing to key suppliers to improve lead-time reliability. Strengthen cybersecurity and device management as IoT coverage expands. For policy makers and enterprise owners, fund digital infrastructure, set data standards, and support vendor-neutral interoperability to reduce integration frictions in public manufacturers. Future work should use longitudinal or quasi-experimental designs, triangulate survey scores with system logs to reduce common-method bias, and test mediation paths from sensing to planning to execution to isolate where the largest gains arise.

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