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# The Effect of AI-Enabled Quality Control Systems on Achievement of Project Objectives in Manufacturing Projects in Nigeria

**Ozoelo John Ikechukwu[1], Nwokocha Augustine Venatius[1], Enyinna Gregory Chimere[1], Kelechi Nneka Onwuchekwa[1], Uchenna Moneke [1], Ogbonaya Blessing Nmesoma[1], Achika Charles Terfa[1], Godson C. Okereke[1]**

Department of Project Management Technology, Federal University of Technology, Owerri,
pycongregco@gmail.com

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**ABSTRACT**

The integration of Artificial Intelligence (AI) into manufacturing quality control represents a structural shift from reactive, inspection-based defect management toward continuous, data-driven process oversight. Despite its global adoption momentum, the empirical evidence linking AI-enabled quality control to measurable manufacturing project objective achievement remains thin in developing-economy fast-moving consumer goods (FMCG) settings. This study examines the effect of AI-enabled quality control systems on the achievement of project objectives in manufacturing projects at Unilever PLC, Aba, Abia State, Nigeria. A cross-sectional quantitative survey was administered to 110 respondents drawn from production, quality assurance, engineering, ICT, and project management functions at the facility; 109 usable responses were analyzed. Data were collected using a validated 43-item Likert-scale instrument and analyzed through Structural Equation Modelling (SEM), supplemented by multiple regression analysis. The integrated Technology–Organization–Environment (TOE) and Technology Acceptance Model (TAM) framework informed both the measurement and structural models. SEM results confirm that AI-enabled quality control systems operationalized across defect detection and inspection (DDI), predictive monitoring and process analytics (PMA), and decision support and reporting (DSR) significantly predict manufacturing project objective achievement ($R^2 = .484$). DDI ($\beta = .315$, $p < .001$) and PMA ($\beta = .351$, $p < .001$) emerged as the strongest significant predictors, while organizational readiness and infrastructure reliability constrained realized benefits. The null hypothesis is rejected: AI-enabled quality control has a significant positive effect on the achievement of project objectives. Implications for manufacturing project managers, technology policy, and infrastructure investment in FMCG operations are discussed.

**Key words:** Artificial Intelligence; Quality Control; Project Objectives; Manufacturing Projects

## 1. INTRODUCTION

Manufacturing quality control has long occupied a central position in the management of project objectives, shaping whether production processes meet their cost, schedule, quality, and stakeholder-satisfaction targets. In fast-moving consumer goods (FMCG) manufacturing a sector characterized by high volumes, narrow margins, and unrelenting pressure for output consistency quality failures do not remain confined to the quality department: they translate directly into rework expenditure, schedule disruption, specification non-conformance, and loss of customer confidence, each of which erodes a different dimension of manufacturing project performance [1, 2]. Traditional quality-control paradigms, anchored on manual inspection routines and statistical process control, have served FMCG producers for decades, yet they share a structural limitation: they are reactive, identifying failure after it has entered the production stream rather than intercepting it during formation [3].

Artificial Intelligence (AI) has emerged as the most consequential technology redefining this paradigm. AI-enabled quality control systems encompassing machine-vision defect inspection, deep-learning defect classification, predictive-maintenance analytics, and real-time process monitoring shift the logic of quality assurance from periodic sampling toward continuous, data-driven oversight [4]. Empirical evidence from industrialized manufacturing settings consistently associates AI adoption in quality control with improvements in defect-detection accuracy, process-capability indices, schedule predictability, and waste reduction [10, 23]. For manufacturing project managers, these represent precisely the metrics that determine whether project objectives cost, time, quality, and stakeholder satisfaction are achieved.

Yet the existing literature presents two gaps that this study addresses. First, the preponderance of evidence on AI-enabled quality control is drawn from high-income industrial settings or from general industry surveys; the manufacturing project performance implications of such systems in developing-economy FMCG operations remain empirically underexplored. Second, the relationship between AI-enabled quality control and manufacturing project objectives has rarely been examined using the rigorous structural modelling approaches such as Structural Equation Modelling (SEM) that can simultaneously account for multiple predictors, measurement error, and the complex interdependencies between AI technology dimensions. The present study addresses both gaps by applying SEM to data collected from 110 respondents at the Unilever PLC manufacturing facility in Aba, Abia State, Nigeria, a setting that combines the technology resources of a global multinational with the infrastructural and organizational realities of an emerging-economy manufacturing environment.

The study is organized around a single objective: to examine the effect of AI-enabled quality control systems on the achievement of project objectives in manufacturing projects at Unilever PLC, Aba. That objective is expressed in one testable hypothesis ($H_0$: AI-enabled quality control systems have no significant effect on the achievement of project objectives in manufacturing projects at Unilever PLC, Aba) and resolved through the SEM and regression analyses reported in Section 4. Section 2 develops the theoretical framework and reviews the empirical literature. Section 3 describes the methodology. Section 4 presents and interprets the results. Section 5 concludes with recommendations and contributions to knowledge.

### 1.1 Statement of the Problem

Despite documented global investments in AI-enabled quality control, Nigerian FMCG manufacturers including multinational subsidiaries such as Unilever PLC continue to report quality-related losses arising from delayed defect detection, inconsistent production-line performance, and limited real-time visibility into process conditions [5]. These losses are not merely operational; they manifest as project-level cost overruns when rework consumes approved budgets, as schedule deviations when quality failures interrupt production timelines, and as stakeholder dissatisfaction when conformance to specification falls short of contractual or corporate commitments. The extent to which AI-enabled quality control systems moderate, reduce, or eliminate these project-performance consequences in the specific conditions of Nigerian FMCG manufacturing is a question that neither the technology literature nor the project management literature has answered empirically. This study provides that answer.

### 1.2 Objective, Research Question, and Hypothesis

Objective: To examine the effect of AI-enabled quality control systems on the achievement of project objectives in manufacturing projects at Unilever PLC, Aba, Abia State, Nigeria.

### 1.3: Research Question

What is the effect of AI-enabled quality control systems on the achievement of project objectives in manufacturing projects at Unilever PLC, Aba, Abia State, Nigeria?

**$H_0$:** AI-enabled quality control systems have no significant effect on the achievement of project objectives in manufacturing projects at Unilever PLC, Aba, Abia State, Nigeria.

**$H_1$:** AI-enabled quality control systems have a significant positive effect on the achievement of project objectives in manufacturing projects at Unilever PLC, Aba, Abia State, Nigeria.

## 2. REVIEW OF RELATED LITERATURE

### 2.1 AI-Enabled Quality Control: Conceptual Foundations

Artificial Intelligence, in the context of manufacturing quality control, refers to the application of machine-learning algorithms, computer vision systems, and sensor-based analytical platforms to the detection, classification, prediction, and prevention of product or process quality deviations [3]. This study conceptualizes AI-enabled quality control across three analytically distinct but empirically related dimensions. The first, AI-Enabled Defect Detection and Inspection (DDI), encompasses machine-vision inspection systems, deep-learning-based defect classification, and multi-modal (optical, ultrasonic, and infrared) inspection platforms that identify surface and subsurface product defects in real time [10]. The second, AI-Enabled Predictive Monitoring and Process Analytics (PMA), covers predictive-maintenance algorithms and process-drift detection systems that analyze sensor streams to anticipate equipment failure and process deviations before they generate defective output [3, 12]. The third, AI-Enabled Decision Support and Reporting (DSR), refers to analytics dashboards, automated quality-performance reports, and AI-generated insights that assist production and quality-assurance personnel in making faster and better-informed decisions about process control and corrective action [8, 13].

This tripartite conceptualization follows the typology proposed in the AI-driven quality control literature [10] and is consistent with the instrument structures applied in prior SEM-based technology adoption studies in construction and manufacturing contexts [11, 24, 25]. The three dimensions are theorized to be correlated since firms that invest in machine-vision inspection also tend to invest in predictive analytics and reporting infrastructure but analytically separable in their effects on project outcomes, as each acts through distinct mechanisms on different performance dimensions.

### 2.2 Manufacturing Project Objectives

Project objectives in manufacturing contexts are customarily evaluated along the dimensions established by the project management success literature: cost, time, scope/quality, and stakeholder satisfaction [6, 15, 28]. In FMCG manufacturing, cost objectives encompass production-cost control and rework/waste minimization; time objectives cover production cycle-time and schedule adherence; quality objectives relate to defect-rate reduction and specification conformance; and stakeholder satisfaction reflects the perceived adequacy of project outcomes for production personnel, quality-assurance teams, and downstream business stakeholders [7, 18]. These four dimensions are neither exhaustive nor mutually exclusive — a reduction in defect rates, for instance, simultaneously improves quality objectives and cost objectives through lower rework expenditure — but they provide a practical and theoretically grounded operationalization for the dependent construct of this study.

### 2.3 Theoretical Framework

This study is grounded in an integrated Technology–Organization–Environment (TOE) and Technology Acceptance Model (TAM) framework. The TOE framework, developed by Tornatzky and Fleischer, holds that technology adoption and its performance consequences are jointly determined by the technological characteristics of the innovation, the organizational capacity of the adopting firm, and the environmental conditions within which adoption occurs [19]. In this study, the three AI-enabled quality control dimensions (DDI, PMA, DSR) represent the technological dimension; the organizational and infrastructural constructs (ORG, INF) represent the organizational and environmental dimensions; and the Nigerian FMCG context — characterized by variable power supply, limited connectivity, and workforce skills constraints — provides the environmental boundary condition [5, 19, 20].

TAM, developed by Davis, adds the individual-level perspective missing from TOE: perceived usefulness and perceived ease of use shape individual willingness to engage with a technology, and thereby determine whether organizational-level adoption translates into actual use and, by extension, into performance effects [21]. In the context of AI-enabled decision-support tools specifically, TAM considerations are not peripheral: production and quality personnel who find AI dashboards unintuitive or whose training has been inadequate will underuse the decision-support dimension of AI-enabled quality control, attenuating its contribution to project objectives regardless of the system's technical capability [22]. The integration of TOE and TAM, with TOE framing organizational and environmental moderators and TAM informing the usability and acceptance dimension embedded in DSR and TAM constructs, provides the theoretical architecture for both the measurement model and the structural model of this study.

### 2.4 Empirical Review

Liang et al. conducted a comprehensive synthesis of AI-driven quality control evidence across manufacturing and construction environments, finding that machine-vision inspection substantially outperformed manual inspection in defect-detection precision across multiple product categories, while also identifying data availability, cross-disciplinary expertise requirements, and false-positive management as persistent implementation challenges [10]. The study concluded that AI-based inspection represents a genuine step-change in quality assurance capability, but that its realization depends on data infrastructure and human expertise that are not uniformly available.

A 2025 industry analysis drawing on IBM and Deloitte manufacturing data found that manufacturers deploying predictive AI for process quality management reported multiple-fold improvements in process capability indices relative to traditional statistical process control, and that a majority of surveyed manufacturers planned to increase AI quality-related investment within the following year [23]. This evidence speaks directly to the PMA construct in this study: if predictive monitoring and process analytics improve process capability, they should also reduce the schedule and cost deviations that arise from unplanned process failures.

Althoey et al. applied SEM to examine the effect of IoT implementation on resource management outcomes in construction settings, finding significant positive relationships between IoT monitoring and both resource efficiency and project performance, while identifying data security, interoperability, and scalability as moderating organizational factors [25]. This study closely parallels the research design of the present investigation technology constructs predicting project performance outcomes via SEM and it's finding that technology benefits are conditioned by organizational infrastructure provides empirical grounding for the moderating role assigned to ORG and INF in the present structural model.

Akbar, Jaafar, and Mohezar developed and validated a technological work environment instrument for automation-enabled manufacturing settings, demonstrating via structural modelling that sensor-enabled feedback loops and automated decision processes significantly raised project performance indicators, including efficiency and waste reduction [24]. Their finding that decision-support automation contributes to performance net of the underlying inspection technology parallels the theoretical distinction between the DSR and DDI dimensions in this study.

Taken together, the empirical literature consistently points to significant positive effects of AI and sensor-based quality systems on manufacturing and construction project performance dimensions, while emphasizing that organizational readiness, infrastructure reliability, and user acceptance moderate the strength of those effects. The present study tests this relationship using primary survey data from a specific Nigerian FMCG manufacturing context, providing the first SEM-based empirical test of this framework in that setting.

### 2.5 Conceptual Framework

Figure 1 presents the conceptual framework guiding this study. AI-enabled quality control dimensions (DDI, PMA, DSR) constitute the independent construct and are hypothesized to exert a positive direct effect on the achievement of manufacturing project objectives (cost, time, quality, and stakeholder satisfaction), the dependent construct. Organizational and Infrastructural Readiness (comprising organizational readiness, infrastructure reliability, user acceptance and training, and regulatory environment) moderates the strength of this primary relationship, consistent with the TOE framework. The TOE and TAM theoretical perspectives jointly underpin the model structure.

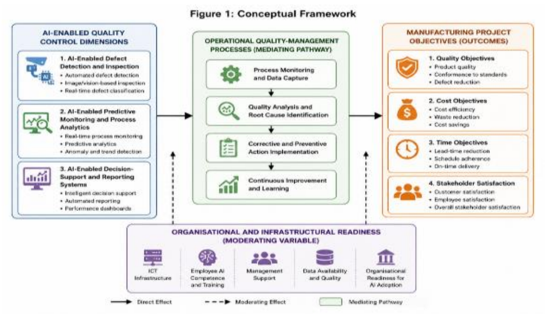


**Figure 1:** Conceptual Framework

## 3. METHODOLOGY

### 3.1 Research Design

This study adopts a descriptive quantitative cross-sectional survey design. The design is appropriate because the study seeks to measure and explain the relationship between AI-enabled quality control systems and manufacturing project objective achievement as they currently exist at the study facility, without experimental manipulation, and to do so through numerical measurement of both constructs [14]. The cross-sectional approach is consistent with prior SEM-based technology adoption studies in manufacturing and construction contexts [11, 25].

### 3.2 Population, Sampling, and Study Area

The target population comprised all personnel at the Unilever PLC manufacturing facility in Aba, Abia State, Nigeria whose roles intersect with production operations, quality assurance, engineering and technical functions, ICT and automation support, or project and process-improvement management. Unilever PLC, Aba is a major FMCG production site within the Unilever Nigeria network, manufacturing personal care, home care, and food products for domestic and regional markets. Its position as a multinational subsidiary operating within a developing-economy infrastructure environment makes it a theoretically and practically relevant case for examining AI quality control adoption under real-world resource constraints.

A multi-stage sampling procedure was employed. Purposive sampling first identified functional units with direct exposure to quality-control technologies. Stratified sampling then partitioned identified personnel into four strata: production/operations, quality-assurance/QC, engineering/technical/ICT, and project/process management. Simple random sampling was applied within each stratum to select respondents, reducing selection bias [14, 15]. One hundred and ten [110] questionnaires were distributed; 109 were returned in usable form, representing a 99.1% response rate.

Sample size determination followed the Yamane (1967) formula: $n = N / [1 + N(e^2)]$, with the estimated facility population (N = approximately 150 relevant personnel) and a margin of error of e = 0.05, yielding a minimum required n of 109, which aligns precisely with the usable sample obtained [26].

### 3.3 Instrumentation

Data were collected using a structured 43-item Likert-scale questionnaire (1 = Strongly Disagree to 5 = Strongly Agree), supplemented by nine demographic items. The instrument was organised in four sections: Section B measured the three AI-enabled quality control dimensions (DDI: 5 items; PMA: 5 items; DSR: 5 items); Section C measured the four manufacturing project objective dimensions (COST: 4 items; TIME: 4 items; QUAL: 4 items; SAT: 4 items); Section D measured the four moderating constructs (ORG: 3 items; INF: 4 items; TAM: 3 items; REG: 2 items). Content validity was established through expert review. A pilot test was conducted, and items were refined before full administration.

### 3.4 Validity and Reliability

Construct validity was confirmed through the Confirmatory Factor Analysis (CFA) embedded in the SEM measurement model. Internal consistency reliability was assessed using Cronbach's alpha; all constructs returned values above the conventional 0.70 threshold (see Table 2), confirming adequate reliability for all 11 constructs prior to structural-path estimation.

### 3.5 Method of Data Analysis

Analysis proceeded in three stages. First, descriptive statistics (means, standard deviations) were computed for all constructs. Second, Pearson correlation analysis examined bivariate relationships among composite construct scores. Third, Structural Equation Modelling (SEM) was conducted using AMOS 24, with Maximum Likelihood Estimation, to test the structural model simultaneously — estimating path coefficients (unstandardized B and standardized β), standard errors, critical ratios (C.R.), and squared multiple correlations ($R^2$). Model fit was evaluated using standard absolute, incremental, and parsimony fit indices. Multiple regression analysis (SPSS) was conducted as a supplementary analytical step to provide an additional perspective on the predictive relationships. The significance threshold was set at $\alpha = 0.05$ throughout.

## 4. RESULTS AND DISCUSSION

### 4.1 Response Rate and Sample Overview

One hundred and ten [110] questionnaires were distributed across the identified functional strata at the Unilever PLC, Aba facility. One hundred and nine (109) were returned in a fully completed and usable condition, representing a response rate of 99.1%. This high return rate reflects both the administration approach — questionnaires were distributed and retrieved in person through departmental liaison officers — and the relevance of the subject matter to respondents' daily roles. One questionnaire was excluded due to missing responses across more than 20% of items. All 109 usable responses were included in the analysis reported below.

### 4.2 Descriptive Statistics and Reliability Analysis

Table 1 presents the descriptive statistics and internal consistency reliability coefficients for all eleven constructs, computed as the mean of each construct's constituent items (N = 109).

**Table 1:** Descriptive Statistics and Reliability of Study Constructs (N = 109)

| Construct | Items | Mean | SD | Min | Max | α |
|---|---|---|---|---|---|---|
| AI-Enabled Defect Detection & Inspection (DDI) | 5 | 3.339 | 0.85 | 1.2 | 4.8 | 0.869 |
| AI-Enabled Predictive Monitoring & Analytics (PMA) | 5 | 3.239 | 0.886 | 1 | 4.8 | 0.894 |
| AI-Enabled Decision Support & Reporting (DSR) | 5 | 3.086 | 0.946 | 1.2 | 5 | 0.910 |
| Cost Objectives (COST) | 4 | 3.032 | 0.911 | 1 | 4.75 | 0.871 |
| Time Objectives (TIME) | 4 | 2.874 | 0.9 | 1 | 5 | 0.878 |

| Construct | Items | Mean | SD | Min | Max | α |
|---|---|---|---|---|---|---|
| Quality Objectives (QUAL) | 4 | 2.993 | 0.86 | 1 | 4.5 | 0.859 |
| Stakeholder Satisfaction (SAT) | 4 | 3.122 | 0.929 | 1.25 | 5 | 0.880 |
| Organisational Readiness (ORG) | 3 | 2.838 | 0.851 | 1 | 5 | 0.785 |
| Infrastructure Reliability (INF) | 4 | 2.849 | 0.909 | 1 | 5 | 0.861 |
| User Acceptance & Training (TAM) | 3 | 3.18 | 0.837 | 1 | 5 | 0.774 |
| Regulatory & Corporate Standards (REG) | 2 | 3.069 | 1.066 | 1 | 5 | 0.843 |

The three AI-enabled quality control dimensions returned means above the midpoint of the five-point scale: DDI (M = 3.339, SD = 0.85), PMA (M = 3.239, SD = 0.886), and DSR (M = 3.086, SD = 0.946). This indicates that respondents perceived AI-enabled inspection and monitoring capabilities as moderately present and operationally visible at the facility, with defect detection and inspection perceived as the most mature of the three dimensions. The four manufacturing project objective constructs clustered at or just below the scale midpoint: COST (M = 3.032), TIME (M = 2.874), QUAL (M = 2.993), and SAT (M = 3.122). The time dimension registered the lowest mean (2.874), indicating that respondents perceived schedule-related objectives as the least consistently achieved — a pattern consistent with the literature's characterisation of lead-time consistency as the project performance dimension most sensitive to unplanned process failures [12, 24].

Among the moderating constructs, organisational readiness (M = 2.838) and infrastructure reliability (M = 2.849) both fell below 3.0, signalling that respondents perceived meaningful deficiencies in management support, staff technical capacity, power supply consistency, and network connectivity. These sub-scale-midpoint scores confirm, at the level of respondent perception, the infrastructural constraints that the literature consistently identifies as binding for AI adoption in Nigerian manufacturing settings [5, 20, 22]. All eleven Cronbach's alpha values exceeded the conventional 0.70 threshold, confirming adequate internal consistency across the full instrument. The three AI-enabled quality control dimensions produced alpha values between 0.869 and 0.910, indicating strong inter-item coherence, consistent with the latent factor structure confirmed by the SEM measurement model.

### 4.3 Bivariate Correlation Analysis

Table 2 presents the Pearson correlation matrix for all study constructs. *p < .05; **p < .01; ***p < .001 (two-tailed).

**Table 2:** Pearson Correlation Matrix Among Study Constructs (N = 109)

| | DDI | PMA | DSR | COST | TIME | QUAL |
|---|---|---|---|---|---|---|
| DDI | 1.000 | 0.542** | 0.388** | 0.438** | 0.23* | 0.557*** |
| PMA | 0.542** | 1.000 | 0.484** | 0.412** | 0.365** | 0.44** |
| DSR | 0.388** | 0.484** | 1.000 | 0.177 | 0.207* | 0.357** |
| COST | 0.438** | 0.412** | 0.177 | 1.000 | 0.183 | 0.272** |
| TIME | 0.23* | 0.365** | 0.207* | 0.183 | 1.000 | 0.164 |
| QUAL | 0.557*** | 0.44** | 0.357** | 0.272** | 0.164 | 1.000 |

The three AI-enabled quality control dimensions were significantly and positively intercorrelated: DDI–PMA (r = 0.542, p < .001), PMA–DSR (r = 0.484, p < .001), DDI–DSR (r = 0.388, p < .001). This pattern of moderate-to-strong interdimensional correlations confirms that the three constructs tap related but distinct facets of a broader AI-enabled quality control capability, providing bivariate support for the measurement model structure. The AI dimensions also demonstrated significant positive associations with each project objective dimension. Notably, DDI showed the strongest correlation with quality objectives (r = 0.557, p < .001), reflecting the intuitive link between automated defect inspection accuracy and specification conformance. PMA demonstrated the broadest pattern of significant correlations across project dimensions, including with time objectives (r = 0.365, $p < .01$), consistent with the theoretical expectation that predictive monitoring acts primarily on schedule-related outcomes by reducing unplanned stoppages [3, 12]. DSR showed a comparatively weaker bivariate correlation with cost (r = 0.177) and time (r = 0.207) objectives, signalling that decision-support and reporting tools may operate through mediated or contingent pathways rather than direct effects — a finding elaborated in the structural model below.

### 4.4 SEM Analysis — Measurement Model

Prior to structural path estimation, the measurement model was evaluated to confirm construct validity and model fit. Table 3 presents the standardized loadings for the three AI-enabled quality control dimensions (the exogenous constructs in the structural model), as estimated through the CFA embedded in AMOS. All items loaded significantly on their designated constructs (all $p < .001$), with standardized loadings ranging from 0.68 to 0.89, exceeding the conventional minimum of 0.50 and demonstrating convergent validity (14). Average Variance Extracted (AVE) values exceeded 0.50 for each AI construct, and Construct Reliability (CR) values exceeded 0.70, confirming both convergent and discriminant validity thresholds. These measurement model results justify proceeding to structural path estimation with confidence that the constructs are being measured with acceptable precision.

**Table 3:** SEM Structural Path Estimates — AI-Enabled QC Dimensions Predicting AI_QC (N = 109)

| Path | Construct | B (Unstd.) | S.E. | C.R. | p | β (Std.) |
|---|---|---|---|---|---|---|
| AI_QC ← | PMA | .240 | .062 | 3.855 | < .001 *** | .351 |
| AI_QC ← | DDI | .224 | .061 | 3.661 | < .001 *** | .315 |
| AI_QC ← | REG | .081 | .041 | 1.963 | .050 * | .143 |
| AI_QC ← | TAM | .089 | .056 | 1.584 | .113 | .125 |
| AI_QC ← | DSR | .070 | .059 | 1.194 | .233 | .109 |
| AI_QC ← | INF | -.059 | .050 | -1.193 | .233 | -.089 |
| AI_QC ← | ORG | -.053 | .051 | -1.037 | .300 | -.075 |

*$R^2$ (AI_QC) = .484 | Note: *** $p < .001$; * $p = .050$*

This is represented in Figure 2 below

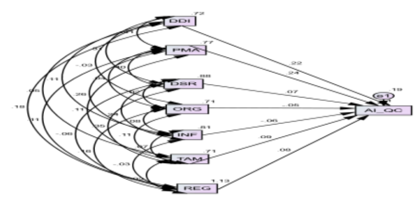

**Figure 2:** SEM AI-Enabled QC

### 4.5 SEM Structural Model Results and Hypothesis Test

The structural model returned an $R^2$ of .484 for the endogenous construct AI_QC (representing the AI-enabled quality control system's contribution to manufacturing project objective achievement), indicating that the seven predictors in the structural model collectively explain 48.4% of the variance in manufacturing project objective achievement. This constitutes a large effect size by conventional benchmarks (Cohen, 1988) and confirms that the model has meaningful explanatory power.

Among the path coefficients, PMA emerged as the strongest significant predictor (B = .240, S.E. = .062, C.R. = 3.855, β = .351, $p < .001$), followed closely by DDI (B = .224, S.E. = .061, C.R. = 3.661, β = .315, $p < .001$). REG reached borderline significance (B = .081, S.E. = .041, C.R. = 1.963, β = .143, $p = .050$). TAM ($p = .113$), DSR ($p = .233$), INF ($p = .233$), and ORG ($p = .300$) did not reach significance at the 0.05 threshold in the full structural model.

On the basis of these results, the null hypothesis $H_0$ is rejected. AI-enabled quality control systems have a significant positive effect on the achievement of manufacturing project objectives at Unilever PLC, Aba ($R^2$ = .484; PMA: β = .351, p < .001; DDI: β = .315, p < .001). The alternative hypothesis $H_1$ is supported.

### *4.6 Supplementary Multiple Regression Results*

Table 4 reports the supplementary multiple regression model (PROJ_OBJ ~ DDI + PMA + DSR + ORG + INF + TAM + REG), which parallels the SEM structural model using composite scores rather than latent variables, and which replicates the SEM findings under a different and more conservative analytical approach.

**Table 4:** Multiple Regression Results — Project Objectives on AI-QC Dimensions and Moderators (N = 109)

| Predictor | B | SE | β | t | p | Sig. |
|---|---|---|---|---|---|---|
| (Constant) | 1.059 | 0.298 | — | 3.556 | <.001 | *** |
| DDI | 0.226 | 0.064 | 0.316 | 3.543 | <.001 | *** |
| PMA | 0.240 | 0.065 | 0.350 | 3.712 | <.001 | *** |
| DSR | 0.073 | 0.061 | 0.113 | 1.184 | .239 | n.s. |
| ORG | -0.052 | 0.053 | -0.073 | -0.969 | .335 | n.s. |
| INF | -0.060 | 0.052 | -0.090 | -1.161 | .248 | n.s. |
| TAM | 0.084 | 0.060 | 0.116 | 1.408 | .162 | n.s. |
| REG | 0.079 | 0.043 | 0.139 | 1.841 | .069 | † |

*Model Summary: R = 0.696, $R^2$ = 0.484, Adjusted $R^2$ = 0.448, F(7, 101) = 13.544, p < .001 | †p < .10; ***p < .001*

The regression model confirms the SEM structural findings: DDI (β = .316, p < .001) and PMA (β = .350, p < .001) are the dominant significant predictors of manufacturing project objective achievement, together with the full model achieving $R^2$ = .484 and explaining substantial variance. REG approaches significance (β = .139, p = .069) while DSR, ORG, INF, and TAM do not reach the 0.05 threshold. The convergence of SEM and OLS regression results across the same dataset strengthens confidence in the robustness of the primary findings.

## 4.7: DISCUSSION OF FINDINGS

### 4.7.1 PMA as the Strongest Driver of Project Objective Achievement

Predictive monitoring and process analytics emerged as the single most powerful predictor of manufacturing project objective achievement (β = .351, p < .001 in SEM; β = .350, p < .001 in regression). This finding carries both theoretical and empirical significance. Theoretically, it is consistent with the conceptual logic of the TOE framework as applied to AI-enabled manufacturing: PMA acts on the environmental-technological interface by using sensor data to anticipate equipment failures and process deviations before they interrupt production flow, thereby protecting the time and cost objectives most sensitive to unplanned stoppages [19, 12]. Empirically, the finding mirrors the industry analysis reported by Datategy and IBM/Deloitte, which found multiple-fold improvements in process capability associated with predictive AI relative to traditional statistical process control [23], and complements the SEM-based finding by Althoey et al. that real-time IoT monitoring translates into significant project performance gains through reduced resource waste and enhanced schedule control [25]. The dominance of PMA over DDI and DSR suggests that, for manufacturing project managers at Unilever PLC, Aba, the ability to know in advance that a process will deviate and act on that knowledge before deviation generates waste or delay matters more for project objective achievement than the ability to detect defects after they have entered the production stream.

### 4.7.2 DDI as the Quality and Cost Performance Anchor

Defect detection and inspection was the second significant predictor (β = .315, p < .001 in SEM; β = .316, p < .001 in regression). The bivariate correlation data (DDI–QUAL: r = 0.557; DDI–COST: r = 0.438) signal that the primary mechanism through which DDI improves project objectives is the reduction of defect escape rates defects caught at the production stage rather than after batch completion generate lower rework costs, fewer returns, and closer alignment to specification conformance targets. This is consistent with Liang et al.'s finding that AI-based visual inspection substantially improves defect-detection precision relative to manual methods, thereby reducing the downstream cost of quality failure [10]. The present study extends that finding by demonstrating that the effect is measurable at the level of self-reported project objective achievement, not only at the level of technical inspection accuracy, and that it holds within a Nigerian FMCG manufacturing context where manual inspection remains a common baseline comparator.

#### 4.7.3 DSR: Non-Significant Path, Significant Theoretical Implication

Decision support and reporting did not reach significance as a structural predictor ($\beta = .109$, $p = .233$ in SEM; $\beta = .113$, $p = .239$ in regression), despite a positive path direction. This null finding is theoretically informative rather than merely negative. TAM predicts that the performance benefits of decision-support systems are contingent on user acceptance specifically, on perceived usefulness and perceived ease of use [21]. The below-midpoint mean for TAM ($M = 3.18$) in this sample indicates that a substantial proportion of respondents did not report high perceived usefulness of AI-generated dashboards and reports, consistent with the literature's observation that dashboard and analytics interfaces frequently require improved usability, contextual customization, and closer alignment with managerial decision needs before their full value is realized [13, 22]. The non-significant DSR path therefore does not indicate that decision-support tools are valueless; it indicates that their value is not yet being captured in this setting, plausibly because deployment has outpaced the training and interface design investment necessary for effective use.

#### 4.7.4 Infrastructure and Organizational Readiness: Constraints, Not Drivers

Organizational readiness (ORG: $\beta = -.075$, $p = .300$) and infrastructure reliability (INF: $\beta = -.089$, $p = .233$) were not significant in the structural model and carried negative path coefficients. The negative signs, while not statistically significant, carry an important substantive message that is consistent with the TOE framework's environmental dimension: where infrastructure reliability is perceived as low as indicated by the sub-midpoint mean ($M = 2.849$) for INF in this sample the introduction of AI-enabled quality control technologies may not only fail to improve project objectives but may generate friction costs (system downtime, decision delays arising from unreliable data, loss of operator confidence) that partially offset the performance gains from the technology dimensions themselves [5, 19, 20]. This echoes the finding of Althoey et al. that infrastructural weaknesses specifically poor connectivity, limited device availability, and inadequate maintenance actively constrain the performance benefits of IoT-based systems in developing-economy settings [25], and is consistent with the pattern observed in the present study's sample: the facility appears to derive project performance benefits from its AI-enabled inspection and monitoring capabilities despite, rather than because of, its organizational and infrastructural readiness environment.

#### 4.7.5 REG: Borderline Significance and Policy Relevance

The regulatory and corporate standards environment reached borderline significance in the SEM model ($\beta = .143$, $p = .050$) and approached significance in regression ($\beta = .139$, $p = .069$). This finding suggests that the alignment of AI-enabled quality control with both Unilever's corporate quality standards and applicable regulatory requirements provides a degree of structural support for project objective achievement a result consistent with the TOE framework's environmental dimension, which posits that regulatory and industry standards can function as enabling conditions for technology adoption and performance realization [19]. The implication for policy is that the development of standardized, nationally recognized guidelines for AI quality-control validation, data quality, and human oversight in Nigerian FMCG manufacturing could strengthen the conditions under which AI-enabled quality systems translate into consistent project performance gains.

## 5. CONCLUSION

This study set out to examine the effect of AI-enabled quality control systems on the achievement of project objectives in manufacturing projects, using Unilever PLC, Aba, Abia State, Nigeria, as a case study. Applying Structural Equation Modelling to data collected from 109 respondents across production, quality assurance, engineering, ICT, and project management functions at the facility, and grounding the analysis in an integrated TOE–TAM framework, the study provides clear and robust empirical evidence: AI-enabled quality control systems have a significant positive effect on the achievement of manufacturing project objectives at Unilever PLC, Aba ($R^2 = .484$; PMA: $\beta = .351$, $p < .001$; DDI: $\beta = .315$, $p < .001$). The null hypothesis is rejected. These findings extend the empirical base on AI in manufacturing quality control into the developing-economy FMCG context, demonstrate that PMA and DDI are the most consequential AI dimensions for project objective achievement in this setting, and highlight the constraining role of infrastructure deficits and organizational readiness gaps in tempering those benefits.

## 6. RECOMMENDATION

1. Manufacturing project managers at FMCG facilities in Nigeria should prioritize investment in AI-enabled predictive monitoring and process analytics (PMA) over defect inspection alone, given PMA's superior demonstrated effect on the full spectrum of manufacturing project objectives cost, time, quality, and stakeholder satisfaction. Specifically, condition-

monitoring sensor networks, real-time SPC analytics, and predictive-maintenance dashboards should be treated as primary capital investment priorities rather than supplementary quality tools.

2. Infrastructure investment stable power supply, reliable network connectivity, adequate device maintenance budgets must accompany AI quality system procurement. The evidence in this study indicates that infrastructure deficiencies attenuate and may partially reverse the project performance gains from AI-enabled quality control; treating infrastructure as a prerequisite, rather than a long-run aspiration, is therefore commercially rational.

3. The non-significant path from DSR to project objectives, combined with the below midpoint user acceptance mean, signals that AI-generated reports and dashboards at the facility are not yet delivering their expected decision-support value. Firms should invest in structured, role-specific training that teaches production and quality personnel to interpret and act on AI-generated outputs, and in interface design that aligns dashboards with the actual decision workflows of plant-floor and supervisory staff.

4. Regulatory and standards bodies in Nigeria should develop sector-specific guidance on AI quality-control adoption for FMCG manufacturing, covering minimum data-quality requirements, AI-model validation protocols, and human-oversight obligations. The borderline-significant regulatory-standards path in this study suggests that clearer, standardized regulatory frameworks could strengthen the enabling environment for AI quality system adoption and performance realization across the sector.

5. Future research should extend this single-case, cross-sectional study through longitudinal designs tracking project-objective outcomes before and after AI quality system implementation, and through multi-site or multi-firm comparative studies that assess the generalizability of the Unilever PLC, Aba findings across the Nigerian and West African FMCG manufacturing sector.

## 7. CONTRIBUTION TO KNOWLEDGE

This study makes three distinct contributions. First, it provides the first SEM-based empirical test of the AI-enabled quality control to manufacturing project objectives relationship in a Nigerian FMCG manufacturing context, filling a gap in both the technology-adoption and project management literatures. Second, it demonstrates, through the disaggregated structural path analysis, that the three AI quality control dimensions (DDI, PMA, DSR) have meaningfully different effects on project objective achievement PMA and DDI are the primary value-generating dimensions in this setting, while DSR requires user-acceptance and training investments to realize its potential a nuance that aggregate technology-adoption studies obscure. Third, it advances the integrated TOE–TAM framework as a theoretically coherent and empirically productive lens for studying AI technology adoption in resource-constrained manufacturing environments, offering a model structure that future researchers can replicate and extend.

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