

# Assessing Organizational Readiness for AI-Enabled Total Quality Management in Nigerian Construction Firms

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## Abstract

This study explores the organisational readiness of Nigerian construction contracting firms for the integration of Artificial Intelligence (AI) into Total Quality Management (TQM) systems. Adopting a quantitative approach, data were collected through a structured questionnaire and analysed using descriptive statistics and inferential statistics. The study evaluates key readiness dimensions, including technological infrastructure, data governance, workforce skills, leadership commitment, regulatory environment, cultural attitudes, and financial capacity. These dimensions are conceptualized within the Technology Organization Environment (TOE) framework as an organizing lens. Findings indicate a moderate level of readiness across the sector, with notable variation observed among small, medium, and large firms. Technological infrastructure and TQM maturity show comparatively higher readiness, while gaps exist in data management, workforce competencies, and regulatory clarity. Inferential analysis suggests differences across firm sizes in workforce skills, cultural attitudes, TQM practices, and supply chain integration. The study provides contextual, analytic perceptions from a developing economy setting and offers preliminary insights for industry stakeholders and policymakers seeking to support AI-enabled quality management in construction.

**Keywords:** Artificial Intelligence (AI); Total Quality Management (TQM); Organizational Readiness; Construction Industry, Nigeria

## 1. Introduction

The construction industry is undergoing a significant paradigm shift driven by rapid advancements in digital technologies, increasing demand for efficiency, and the imperative for sustainable infrastructure delivery (Eze & Chinedu, 2020). Within this evolving landscape, Artificial Intelligence (AI) has emerged as a transformative force with the potential to redefine traditional construction practices, particularly in the domain of quality management. In Nigeria, where the construction sector plays a critical role in economic development, employment generation, and infrastructure provision, persistent challenges such as cost overruns, project delays, poor quality outcomes, and inefficient processes continue to undermine performance (Ibrahim et al., 2024; Okwe, 2024). These systemic inefficiencies highlight the urgent need for innovative approaches to enhance productivity and quality assurance.

Total Quality Management (TQM), a well-established management philosophy centred on continuous improvement, customer satisfaction, and process optimisation, has been widely recognised as a critical driver of performance in construction organisations. However, the effectiveness of TQM in the Nigerian construction industry remains constrained by inconsistent implementation, limited data utilisation, and inadequate integration of digital technologies

(Bamgbose et al., 2024). The integration of AI and TQM referred to as AI-enabled TQM offers a promising pathway to address these limitations by embedding intelligent automation, predictive analytics, and data-driven decision-making into quality management systems.

AI technologies such as machine learning, computer vision, and predictive analytics have demonstrated significant potential in enhancing construction processes, including automated defect detection, risk prediction, real-time monitoring, and optimisation of resource allocation (Adamu et al., 2024). Globally, the adoption of AI in construction is accelerating, driven by the need to improve efficiency, reduce waste, and enhance safety. However, despite growing awareness, the adoption of AI in the Nigerian construction sector remains at an early stage, hindered by infrastructural deficiencies, skills gaps, regulatory uncertainties, and cultural resistance to change (Onyia et al., 2024). Recent policy initiatives, including Nigeria's National Artificial Intelligence Strategy and the National Digital Economy Policy, underscore the government's commitment to fostering digital transformation and innovation across sectors (NITDA, 2025; Federal Ministry of Communications and Digital Economy, 2020). Nonetheless, translating these strategic ambitions into practical implementation within construction firms requires a comprehensive

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understanding of organisational readiness. This readiness extends beyond technological capability to encompass workforce competence, leadership commitment, regulatory alignment, and organisational culture.

This study therefore aims to assess the organisational readiness of Nigerian construction contracting firms for the adoption of AI-enabled TQM. By examining key readiness factors including technological infrastructure, data governance, workforce skills, leadership commitment, regulatory environment, cultural attitudes, and financial capacity the study provides a holistic evaluation of the factors influencing AI-TQM integration. Furthermore, it explores differences in readiness across firm sizes, offering critical insights into how small, medium, and large contractors can strategically position themselves for digital transformation.

## **2. Literature Review**

### **2.1 Total Quality Management (TQM): Principles and Application in the Construction Industry**

Total Quality Management (TQM) is widely recognised as a comprehensive management philosophy aimed at achieving long-term organisational success through continuous improvement, customer satisfaction, and the active involvement of all employees. Rather than functioning as a discrete set of tools, TQM represents an integrated system that embeds quality into organisational culture, processes, and strategic decision-making. The foundational principles of TQM, as articulated by quality pioneers such as Deming, Juran, Crosby, and Ishikawa, emphasise customer focus, process optimisation, employee involvement, fact-based decision-making, and continuous improvement.

Although TQM originated in the manufacturing sector, its application within the construction industry has gained increasing attention over the past two decades. The construction sector, characterised by project-based operations, fragmented supply chains, and bespoke outputs, has historically lagged manufacturing in adopting structured quality management systems. Nevertheless, empirical studies demonstrate that effective implementation of TQM in construction can significantly enhance project performance, reduce defects, improve client satisfaction, and increase organisational efficiency (Ibrahim et al., 2024; Okwe, 2024). The implementation of TQM in developing economies, particularly Nigeria, remains inconsistent. While awareness of TQM principles is relatively high (Olaleye, 2019), practical application is often limited by inadequate technical expertise, weak enforcement of standards, poor communication, and resistance to organisational change (Bamgbose et al., 2024). Furthermore, the limited use of data-driven decision-

making within traditional TQM practices constrains its effectiveness, highlighting the need for integration with emerging digital technologies.

### **2.2 TQM in the Construction Industry: Global Perspectives**

Historically, TQM found its earliest and most widespread application in manufacturing, particularly in Japan and later in the United States, where it led to significant gains in productivity, cost reduction, and product reliability. The construction industry, however, has traditionally lagged in adopting TQM, due to its project-based nature, fragmented supply chains, and the prevalence of bespoke, one-off projects. Key elements of TQM in construction include: Quality Assurance (QA): Systematic processes to ensure that project requirements are met, including the establishment of policies, procedures, standards, and training, Quality Control (QC): The specific implementation of QA through inspections, testing, and corrective actions to identify and rectify defects, Continuous Improvement: Regular review and refinement of processes to eliminate waste, reduce errors, and enhance value, Teamwork and Collaboration: Cross-functional teams involving clients, contractors, designers, and suppliers to foster shared responsibility for quality,

### **2.3 TQM in Nigerian Construction: Current State and Challenges**

In Nigeria, the construction industry is a vital sector, contributing significantly to GDP and national development. However, it faces persistent challenges related to poor quality, structural failures, cost overruns, and project delays (Ibrahim et al, 2024). Literature consistently attributes many of these issues to the lack of strict compliance with TQM principles, inadequate quality management systems, and insufficient training of professionals. Purchasing quality materials, ensuring quality improvement processes, site management responsibility, and monitoring/control of quality are among the most practiced principles, but effective knowledge management and information sharing are less developed.

### **2.4 Artificial Intelligence in Construction: Global and Nigerian Trends**

#### **2.4.1 Global State of AI Adoption in Construction (2020–2025)**

Artificial Intelligence (AI) is rapidly emerging as a transformative force in the construction industry worldwide. According to the Royal Institution of Chartered Surveyors (RICS) Artificial Intelligence in Construction Report (2025), the industry is at an inflection point, with growing data maturity, accessible tools, and mounting pressure for productivity gains creating the conditions for rapid AI adoption. The global AI in construction market is projected to grow from \$4.86 billion in 2025 to \$22.68 billion by 2032, at

a compound annual growth rate of 24.6% (MarketsandMarkets, 2024; Fortune Business Insights, 2024). Despite this optimistic outlook, actual adoption remains limited; as of 2025, approximately 45% of organisations report no use of AI, 34% are in early pilot phases, and less than 1% have achieved full organisation-wide integration (McKinsey & Company, 2024; Deloitte, 2025). While 56% of surveyed investors plan to increase AI-related investments compared to previous years, only about 20% of organisations are actively engaged in strategic planning or proof-of-concept development (PwC, 2024; KPMG, 2025). Key barriers to AI adoption in construction include a lack of skilled personnel (46%), poor data quality (30%), integration challenges (37%), high implementation costs (29%), and unclear return on investment (28%) (McKinsey & Company, 2024; Deloitte, 2025).

#### *2.4.2. AI technologies being adopted in construction include:*

Machine Learning: Used for predictive analytics, risk assessment, cost estimation, and schedule optimization. Computer Vision: Enables automated quality inspection, safety monitoring, progress tracking, and detection through analysis of images and video from drones and site cameras. Robotics and Automation: AI-powered robots perform repetitive tasks such as bricklaying, welding, and material handling, improving productivity and safety. Digital Twins and BIM Integration: AI enhances Building Information Modelling (BIM) and digital twins by enabling real-time monitoring, clash detection, and predictive maintenance.

#### *2.4.3 AI Adoption in the Nigerian Construction Sector*

In Nigeria, the adoption of artificial intelligence (AI) in the construction sector remains at a relatively nascent stage. Existing studies indicate that awareness and practical utilisation of AI technologies among construction firms are still limited, with applications such as computer vision and predictive analytics being the most recognised and adopted (Oke et al., 2023; Onyia et al., 2024). At the policy level, the Nigerian government has demonstrated increasing commitment to digital transformation through initiatives such as the National Digital Economy Policy and Strategy (2020–2030) and the Nigeria Artificial Intelligence Landscape Report (2025), both of which position AI as a strategic driver for economic growth, innovation, and workforce development (Federal Ministry of Communications and Digital Economy, 2020; NITDA, 2025). In practice, leading industry players such as Julius Berger Nigeria Plc have begun piloting AI-enabled solutions across areas including design optimisation, project management, and quality control, utilising tools such as generative design, predictive analytics, and digital twins to improve operational efficiency and sustainability outcomes (Julius Berger Nigeria Plc,

2024). Despite these developments, significant barriers continue to constrain widespread adoption, including inadequate digital infrastructure, limited technical expertise, high implementation costs, poor data quality, and organisational resistance to change (World Bank, 2025; Onyia et al., 2024).

### **2.5 Relationship Between AI and TQM: Enhancing Quality Management Practices**

#### *2.5.1 AI as an Enabler of TQM in Construction*

Artificial intelligence (AI) is positioned to transform Total Quality Management (TQM) practices in construction by enhancing automation, improving decision-making, and enabling continuous improvement processes. By integrating AI into TQM frameworks, firms can address persistent challenges such as human error, process variability, and limited ability to extract insights from large and complex datasets (Sony et al., 2022; Oke et al., 2023). AI-enabled quality inspection tools such as computer vision for defect detection, drones and sensor-based monitoring systems, and real-time analytics are transforming traditional QA/QC processes by enabling early identification of defects and reducing rework (Zhang et al., 2023). Industry applications further demonstrate this potential; for example, platforms such as Buildots and Disperse.io utilize AI-driven site monitoring and analytics to improve project tracking and reduce delays. Overall, AI–TQM integration represents a critical pathway for improving construction quality, efficiency, and sustainability.

#### **2.6 AI Readiness Factors in Construction Contracting Firms**

Organizational readiness for AI adoption in construction is shaped by a complex interplay of organizational, technological, and environmental factors. This study draws on the Technology Organization Environment (TOE) framework, originally proposed by Tornatzky and Fleischer (1990), as a theoretical lens for organising and interpreting these readiness dimensions. The TOE framework suggests that technology adoption in organisations is simultaneously influenced by three contextual clusters: the technological context (the internal and external technologies relevant to the firm), the organisational context (the characteristics and resources of the firm), and the environmental context (the industry, market, and regulatory setting in which the firm operates). Although the TOE framework was originally developed in the context of information technology adoption, it has been widely applied and validated across sectors, including construction and project management, and is well suited to analysing multi-dimensional readiness for AI-enabled systems (Oliveira & Martins, 2011; Eze & Chinedu, 2020).

Within this framework, the eleven readiness factors examined in this study are mapped as follows. Technological **context** encompasses Technological Infrastructure (TI), Data Readiness & Governance (DG), and Cybersecurity & Risk Management (CY) factors that reflect the technical capacity of the firm and its digital environment. The **organisational context** covers Workforce Skills (WS), Leadership Commitment (LC), TQM Practices & Maturity (TQM), and Funding & Investment (FI) factors that reflect internal human, managerial, and financial readiness. The **environmental context** includes Regulatory Environment (RE), Cultural Attitudes (CA), Procurement & Contracts (PC), and Supply Chain & Vendor Ecosystem (SC) factors that capture the external conditions shaping adoption decisions. This mapping provides a theoretically grounded structure for the readiness assessment and guides the interpretation of findings in Section 4. Table 1 in Appendix 1 summarises the current status, challenges, and opportunities associated with each readiness factor.

### 3. Research Methodology

This study adopts a quantitative, exploratory approach to investigate organisational readiness for the integration of Artificial Intelligence (AI) and Total Quality Management (TQM) within Nigerian construction contracting firms. Findings are presented as preliminary evidence. The unit of analysis is the individual respondent, and factor-level means are aggregated across respondents within each firm-size category (large, medium, and small) for comparative purposes. The target population includes construction firms registered with FIRS with tax records within the last 3 years. Key respondents comprise project managers, quality assurance officers and IT managers. Purposive sampling was adopted to select major construction hubs (Lagos, Abuja, Port Harcourt). A minimum of 150 survey respondents was determined using Cochran's formula (95% confidence level, 5% margin of error). Quantitative data was collected using a structured questionnaire based on validated instruments, covering demographics, technological infrastructure, workforce skills, leadership commitment, regulatory environment, and organisational culture. Responses were measured on a 5-point Likert scale. The research instrument was pilot-tested and validated using expert review and

exploratory factor analysis, while reliability was confirmed through Cronbach's alpha ( $\geq 0.70$ ). Quantitative data were analysed using SPSS (descriptive statistics, regression, ANOVA).

### 4. Finding and Discussion

#### Quantitative Analysis of AI-TQM Readiness by Firm Size Using

This section presents an exploratory analysis of a Likert-scale dataset to assess readiness for integrating Artificial Intelligence (AI) into Total Quality Management (TQM) within Nigerian construction contracting firms, comparing large, medium, and small companies. The dataset contains 33 items mapped to 11 readiness factors (TI, DG, WS, LC, RE, CA, TQM, PC, SC, CY, FI), organised within the TOE framework as described in Section 2.6. The Overall Readiness Index (ORI) is calculated as the unweighted arithmetic mean of the 11 factor scores, with each factor score being the mean of its constituent Likert items. Equal weighting is adopted as a transparent baseline appropriate for exploratory work; it does not imply that all factors carry equivalent practical importance, and future studies with larger samples may apply theoretically motivated weighting. ORI values are: Large = 3.286; Medium = 3.386; Small = 3.365 on a 1–5 scale, indicating broadly moderate readiness across all firm types. The lowest mean factor score is Procurement & Contracts (overall mean = 3.103). Exploratory inferential analysis suggests possible between-group differences for Workforce Skills (WS), Cultural Attitudes (CA), TQM Practices & Maturity (TQM), and Supply Chain & Vendor Ecosystem (SC) ( $p < .05$ ), though these patterns should be treated as indicative rather than confirmatory, given the aggregated data structure and small group sizes. However, many factors violate homogeneity of variance (Levene  $p < .05$ ), so Welch ANOVA is reported where appropriate; exploratory differences remain for WS, CA, and TQM under Welch. Given the aggregated data structure ( $n = 3$  groups), all inferential results should be treated as indicative patterns only. The dataset is presented under three headings: Group 1: large-scale construction company, Group 2: medium-scale construction company, Group 3: small-scale construction company (Table 2)

**Table 2:** Factor means (SD) by firm

| Factor                         | Large                | Medium               | Small                |
|--------------------------------|----------------------|----------------------|----------------------|
| TI                             | 3.336 (0.172)        | 3.502 (0.062)        | 3.415 (0.340)        |
| DG                             | 3.337 (0.114)        | 3.817 (0.547)        | 3.337 (0.114)        |
| WS                             | 3.447 (0.091)        | 3.261 (0.045)        | 3.389 (0.110)        |
| LC                             | 3.283 (0.196)        | 3.381 (0.253)        | 3.243 (0.091)        |
| RE                             | 3.134 (0.225)        | 3.223 (0.312)        | 3.500 (0.124)        |
| CA                             | 3.231 (0.340)        | 3.527 (0.108)        | 3.143 (0.163)        |
| TQM                            | 3.576 (0.045)        | 3.385 (0.096)        | 3.277 (0.243)        |
| PC                             | 2.894 (0.563)        | 3.068 (0.217)        | 3.347 (0.070)        |
| SC                             | 3.502 (0.062)        | 3.345 (0.038)        | 3.502 (0.062)        |
| CY                             | 3.033 (0.466)        | 3.367 (0.118)        | 3.506 (0.080)        |
| FI                             | 3.377 (0.075)        | 3.363 (0.211)        | 3.361 (0.069)        |
| <b>Overall Readiness Index</b> | <b>3.286 (0.057)</b> | <b>3.386 (0.073)</b> | <b>3.365 (0.060)</b> |

Source (Field Survey, 2025)

### Key descriptive patterns

Large firms score highest on TQM and SC, and lowest on PC and CY, Medium firms show particularly high DG and CA, but lower WS and SC, Small firms show comparatively high CY, RE, and PC in the post-coded readiness metrics.

### Inferential results: one-way ANOVA across firm sizes

Assumption checks: Levene's test (homogeneity of variance) is significant ( $p < .05$ ) for several factors (DG, WS, CA, TQM, PC, CY, FI), indicating unequal variances. Where Levene is significant, Welch ANOVA is reported as the primary inference statistic (Table 3).

automatically translate into AI-readiness: even where basic connectivity exists, the reliability, bandwidth, and interoperability requirements of AI-driven quality monitoring systems may exceed what current infrastructure provides (Onyia et al., 2024). Data Governance and AI Readiness (TOE: Technology context). Data readiness outcomes are mixed, with medium firms showing an unusually high DG score (mean = 3.817) compared to large and small firms (3.337). While the pattern of data fragmentation identified broadly parallels concerns raised in Nigeria's National AI Strategy regarding data quality and standardisation (NITDA, 2025). TQM Maturity and Firm Size (TOE: Organisational context). TQM factor scores are relatively high and show exploratory evidence of size-group differences (Large > Medium,

**Table 3:** One-way ANOVA across firm sizes (Large vs medium vs Small)

| Factor          | Primary test | F             | p (used)     | $\eta^2$     | Interpretation          |
|-----------------|--------------|---------------|--------------|--------------|-------------------------|
| TI              | ANOVA        | 0.694         | 0.519        | 0.104        | Not significant         |
| DG              | Welch        | 1.728         | 0.244        | 0.372        | Not significant (Welch) |
| WS              | Welch        | <b>9.009</b>  | <b>0.012</b> | <b>0.502</b> | <b>Significant</b>      |
| LC              | ANOVA        | 0.692         | 0.520        | 0.103        | Not significant         |
| RE              | ANOVA        | 3.338         | 0.070        | 0.357        | Not significant (trend) |
| CA              | Welch        | <b>9.407</b>  | <b>0.010</b> | <b>0.397</b> | <b>Significant</b>      |
| TQM             | Welch        | <b>9.971</b>  | <b>0.011</b> | <b>0.449</b> | <b>Significant</b>      |
| PC              | Welch        | 4.616         | 0.062        | 0.261        | Not significant (trend) |
| SC              | ANOVA        | <b>13.390</b> | <b>0.001</b> | <b>0.691</b> | <b>Significant</b>      |
| CY              | Welch        | 4.084         | 0.068        | 0.384        | Not significant (trend) |
| FI              | Welch        | 0.057         | 0.945        | 0.003        | Not significant         |
| Readiness Index | ANOVA        | 3.390         | 0.068        | 0.361        | Not significant (trend) |

Source (Field Survey, 2025)

**Effect size interpretation:**  $\eta^2$  (effect size) values for WS, CA, TQM, SC range from approximately 0.40 to 0.69. Conventional benchmarks would classify these as large effects; however, as the analysis operates on aggregated group means ( $n = 3$  groups) rather than individual respondent data (Table 4)

$p < .05$  under Welch ANOVA). This is broadly consistent with prior Nigerian contractor research suggesting that TQM-practising firms achieve stronger performance outcomes (Ibrahim et al., 2024; Okwe, 2024). The inference that firms with stronger TQM structures are better positioned to embed AI into their

**Table 4:** Post-hoc pairwise differences (significant results only)

| Factor | Method       | Significant pair                                                             | Direction              |
|--------|--------------|------------------------------------------------------------------------------|------------------------|
| WS     | Games–Howell | Large vs Medium ( $p \approx 0.016$ )                                        | Large > Medium         |
| CA     | Games–Howell | Medium vs Small ( $p \approx 0.008$ )                                        | Medium > Small         |
| TQM    | Games–Howell | Large vs Medium ( $p \approx 0.018$ )                                        | Large > Medium         |
| SC     | Tukey HSD    | Large vs Medium ( $p \approx 0.002$ ); Small vs Medium ( $p \approx 0.002$ ) | Large & Small > Medium |

Source (Field Survey, 2025)

Technological Infrastructure scores are moderate to high across firm sizes (3.34–3.50). While this pattern is broadly consistent with national-level indicators of improving broadband penetration and expanding digital infrastructure (NCC, 2024; World Bank, 2025), the study data alone cannot confirm that these national trends have been realised at the firm level. It is also worth noting that moderate TI scores do not

processes (Sony et al., 2022) is theoretically probable but remains untested in the present study and should be the subject of future longitudinal or case-study research

### 5. Conclusion and Further Research

This exploratory study indicates that Nigerian construction firms demonstrate a moderate level of readiness for AI–TQM integration, with comparatively

stronger capabilities in technological infrastructure and TQM maturity but notable gaps in data governance, workforce skills, regulatory clarity, and procurement systems. Readiness varies by firm size, highlighting uneven digital transformation across the sector. The findings are broadly consistent with the Technology Organisation Environment (TOE) framework as a conceptual lens: the pattern of readiness gaps aligns with the framework's proposition that adoption is shaped by technological capacity, organisational resources, and environmental conditions simultaneously. Limitations related to aggregated data, small group sizes, and a cross-sectional design restrict the depth and generalisability of the findings. Future research should use larger, respondent-level datasets, advanced methods (e.g., SEM), and longitudinal designs, while also exploring factor interrelationships, firm-level case studies, emerging technologies (e.g.,

generative AI), and the role of policy frameworks. Overall, effective AI–TQM adoption requires coordinated efforts in technology, skills development, leadership, and institutional reform.

## 6. Recommendations

1. Nigerian construction firms should prioritise investment in robust digital infrastructure and structured data management systems to support AI–TQM integration. Without this foundation, AI adoption will remain limited and ineffective.
2. Firms should implement continuous professional development programmes, collaborate with academic and training institutions, and promote digital literacy across all organisational levels.
- 3.

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## Appendix 1

**Table 1:** AI Readiness Factors

| Readiness Factor                            | Current Status                                                                                                                                                                                    | Challenges                                                                                                                                                 | Opportunities                                                                                                                                                         |
|---------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Technological Infrastructure (TI)</b>    | Broadband penetration at 48.15%; expanding fibre optic and mobile networks; limited AI-specific infrastructure in construction (Nigerian Communications Commission [NCC], 2024; World Bank, 2025) | High cost of AI tools and infrastructure; unreliable power; urban-rural digital divide; integration complexity (Berha & Khemani, 2026; Onyia et al., 2024) | Government and donor investments (e.g., BRIDGE Project); cloud/edge computing; sector-specific AI development (Federal Ministry of Communications, 2026; NITDA, 2025) |
| <b>Data Readiness &amp; Governance (DG)</b> | Fragmented, often unstructured data; NDPR in place; limited data governance capacity (NITDA, 2019; NDPC, 2025)                                                                                    | Poor data quality; lack of structured databases; privacy and security concerns; limited compliance (NITDA, 2019; Federal Republic of Nigeria, 2023)        | Open data initiatives; alignment with international standards; capacity building in data management (NITDA, 2020; World Bank, 2025)                                   |
| <b>Workforce Skills (WS)</b>                | Significant skills gap in AI and digital construction; moderate TQM awareness in large firms (Bamgbose et al., 2024; Ibrahim et al., 2024)                                                        | Shortage of skilled professionals; brain drain; limited access to training; resistance to                                                                  | 3MTT, Microsoft AI Skill Navigator, online courses, integration of AI/TQM in curricula, artisan training                                                              |

| Readiness Factor                                | Current Status                                                                                                            | Challenges                                                                                                               | Opportunities                                                                                                                          |
|-------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
|                                                 |                                                                                                                           | upskilling (World Bank, 2025; Onyia et al., 2024)                                                                        | partnerships (NITDA, 2025; 3MTT, n.d.)                                                                                                 |
| <b>Leadership Commitment (LC)</b>               | Varies; stronger in large firms and government; growing policy support (NITDA, 2025)                                      | Short-term ROI expectations; limited awareness of AI-TQM synergies; resource constraints (Onyia et al., 2024)            | Leadership training; government incentives; pilot projects to build confidence (World Bank, 2025; NITDA, 2025)                         |
| <b>Regulatory Environment (RE)</b>              | National AI Strategy and NDPR in development; ISO standards referenced; fragmented enforcement (NITDA, 2025; NITDA, 2019) | Overlapping jurisdictions; weak enforcement; lack of sector-specific AI guidelines; legal uncertainty (World Bank, 2025) | Unified AI governance frameworks; alignment with global standards; public-private regulatory sandboxes (NITDA, 2025; World Bank, 2025) |
| <b>Cultural Attitudes (CA)</b>                  | Mixed perceptions; growing youth engagement; resistance in SMEs and older workforce (NITDA, 2025)                         | Fear of job loss; scepticism; low digital literacy; trust and transparency concerns (Onyia et al., 2024)                 | Awareness campaigns; success stories; participatory stakeholder engagement; youth-driven innovation (World Bank, 2025)                 |
| <b>TQM Practices &amp; Maturity (TQM)</b>       | Moderate to high in large firms; low in SMEs; linked to improved performance (Ibrahim et al., 2024; Okwe, 2024)           | Inadequate technical expertise; policy inconsistency; lack of incentives; cultural resistance (Okwe, 2024)               | Framework development; capacity building; AI integration to amplify TQM impact (Adamu et al., 2024)                                    |
| <b>Procurement &amp; Contracts (PC)</b>         | Traditional, rigid systems; limited e-procurement adoption (Federal Republic of Nigeria, 2007)                            | Lack of flexibility and transparency; legal and liability issues (Onyia et al., 2024)                                    | E-procurement, smart contracts, legal reforms (Federal Ministry of Information, 2025)                                                  |
| <b>Supply Chain &amp; Vendor Ecosystem (SC)</b> | Emerging local and international vendors; integration challenges (Onyia et al., 2024)                                     | Interoperability, vendor lock-in, support for local standards (Bamgbose et al., 2024)                                    | Innovation hubs, vendor partnerships, open-source platforms (NITDA, 2025)                                                              |
| <b>Cybersecurity &amp; Risk Management (CY)</b> | NDPR and Cybercrimes Act in place; capacity developing (NITDA, 2019; Federal Republic of Nigeria, 2015)                   | Rising cyber threats; limited risk management capacity (NDPC, 2025)                                                      | ISO/IEC 27001 adoption; regular training; risk assessments (World Bank, 2025)                                                          |
| <b>Funding &amp; Investment (FI)</b>            | Government and donor programs; private investment in large firms (World Bank, 2025)                                       | Limited access for SMEs; high cost of digital transformation (Onyia et al., 2024)                                        | Grants, concessional loans, public-private partnerships (World Bank, 2025; Federal Ministry of Communications, 2026)                   |