Scalability, Ethics, and Integration Challenges in AI-Driven Quality Management Systems: Examining the Mediating Role of Cost-Effectiveness

The Journal of Educational Paradigms
2025, Vol. 07(01) 337-343

ISSN (Print): 2709-202X
ISSN (Online): 2709-2038
DOI:10.47609/0701112025

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Abstract

The introduction of Artificial Intelligence (AI) into Quality Management Systems (QMS) is causing the organizations to begin to perceive quality assurance and process improvement in a new way. The given current research focused on the investigation of the impact of three fundamental independent variables, Scalability of AI Integration, Ethical Implications of AI, and AI Integration Challenges, on the Effectiveness of AI-Driven QMS in the context of the Cost-Effectiveness analysis. There was quantitative research methodology through structured questionnaire that was conducted in different classes of industries in Pakistan. The overall valid responses collected and analyzed are 284 and this was done through the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) using R programming environment. The results of structural models indicated that constructs have very significant relationships. Only the mediating effect of cost-effectiveness was positively associated with scalability and ethical practices, but AI integration challenges had a direct positive effect and an indirect effect through cost-effectiveness. The research made both theoretical and practical contributions through validation of a SEM. It provides viable recommendations to quality professionals, policymakers and institutions that aim at having scalable ethical AI practices. The next research can compare various sectors and evaluate the things in the long run to demonstrate how AI will transform the quality systems.

Keywords: Artificial Intelligence, Quality Management Systems, Scalability, Ethics, AI Integration Challenges, Cost-Effectiveness, PLS-SEM, R Programming.

INTRODUCTION

The advent of AI in QMS is altering the way organizations are defining quality assurance, process management, and improving themselves through AI. The quality processes are becoming increasingly linked to AI by automation, accuracy, and efficiency of machine learning, robotics or cognitive computing, every day. The application of AI in QMS is however, constrained by its scalability, ethical preparedness and effective use in various business environments, regardless of the type of opportunities. Even though the interest in AI-based quality systems is growing, scalability and ethical integration are not independent issues that an organization must address. The literature at hand tends to discuss these themes separately; their interaction, especially in the context of cost-effectiveness on the efficacy of AI-based QMS is not thoroughly studied. The study has practical and academic value, as it is part of a relatively new but under-researched field of literature on the ethical scalability of AI in QMS. It addresses a gap in cross-disciplinary literature that exists today, investigating the interaction. It is hoped that the research will offer the top management or executives a blueprint that will be used to gauge their willingness to embrace AI solution practices, which can be scaled at various levels based on their organizational and ethical settings. The findings will assist regulators and policymakers to settle the application of AI applications in functions which have critical quality assurance.

The following are the specific objectives of this research:

- To determine the important aspects of scalability that affect the adoption of AI in QMS.
- To evaluate the ethical considerations related to the AI-based quality management.
- To explore issues associated with the introduction of AI systems into the current quality infrastructure.
- To test the effect of cost-effectiveness between independent and dependent variables.
- To assess the general performance of AI-Driven QMS in industries.

In relation to the objectives the study aims at answering the following questions:

- Which are the major scalability aspects which influence the integration of AI and Quality Management Systems?
- What are some of the variations in these scalability factors across the different industries with various operation requirements?
- What is the contribution of organizational resources and infrastructure to AI-QMS scalability?
- What ethical concerns are the most important when it comes to the use of AI in quality management?
- What are the resolutions provided by organizations to these ethical concerns to ensure that transparency, fairness, and trust in AI-QMS are guaranteed?
- What are the integration problems with the introduction of AI into existing QMS systems?
- How does cost-effectiveness mediate the connection between the challenge of integration, scalability and ethics and the overall effectiveness of AI-driven QMS?
- How effective are AI-based QMS solutions to deliver quantifiable quality improvement in sectors?.

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LITERATURE REVIEW

The use of AI in industry has heightened the need to research the scalability, ethics, cost-effectiveness, and implementation issues, especially in Quality Management Systems (QMS). Nevertheless, the available literature is scattered and mostly technology-focused, but it does not pay much attention to the organizational and ethical aspects. The need of AI-enabled QMS is scalability because data-driven automation is growing, and the data growth rate is exponentially increasing, which is a significant challenge to enable the effective data leveling and scaling of the system (Arinez et al., 2020; Fan et al., 2023). Infrastructure constraints, including the high-speed processing requirements, cybersecurity risks, and interoperability constraints also limit AI deployment. Although Quality 4.0 and cognitive-engineering models suggest universal strategies to improve infrastructural support (Carvalho and Lima, 2022), they are not empirically validated on a large scale. Moreover, the ability to sustain AI performance with growing data volume, diversity, and speed is problematic in the manufacturing, agricultural, and medical industries (Dhal and Kar, 2024; Shaw et al., 2019). The idea of human scalability has not been explored yet because automation transforms workforce roles and skills demand(Hazarika, 2020; Schwendicke et al., 2020), and workforce readiness and reskilling efforts are necessary (Bankins et al., 2024; Arslan et al., 2022). Furthermore, scalability of inferences, which guarantees the reliability of the system over extended workloads, remains a limitation to the adoption. Although it has been suggested that Quality 4.0 and cognitive engineering can be integrated to make multilevel decisions (Carvalho and Lima, 2022; Espina-Romero et al., 2024), few empirical studies have been conducted in the operational QMS context. All in all, the issue of scalability is multidimensional in terms of technical, infrastructural, human, and inferential aspects, which restricts a holistic view of their interaction to determine the effectiveness of AI-based QMS.

The swift use of AI has heightened ethical issues, such as transparency, accountability, privacy, fairness, and human control. Transparency enhances the knowledge of stakeholders and auditability of decisions in AI-based QMS (Carvalho and Lima, 2022), but black-box algorithms make operations difficult. Responsibility is also restricted because there are no standardized traceability and moral responsibility mechanisms (Alzubaidi et al., 2023). Another significant issue is privacy, particularly in digital health, and federated learning is suggested as a partial remedy to this problem. Fairness is concerned with algorithmic bias, but the corrective actions are mostly exploratory and difficult to apply to controlled QMSs (González-Sendino et al., 2024; Ntoutsi et al., 2020). In high-risk situations, ethical compliance is largely dependent on human control (Enqvist, 2023), which exposes a long-standing disparity between normative and operationalized concepts.

Another important consideration in AI adoption is cost-effectiveness which can lower the costs of quality control, enhance operational efficiency, and generate revenue. Nonetheless, the empirical research tends to focus on short-term savings, whereas the empirical data are scarce and industry specific. Financial analysis and cost-benefit analysis remain insufficient, although it has proven to be more productive in healthcare and agri-food sectors (Shin et al., 2025; Taneja et al., 2023; Ta et al., 2024). Strategic investments are assisted by applications like artificial neural networks and decision support systems (Al-Surmi et al., 2022). Other organizational and human obstacles, such as technical illiteracy, fear, leadership void, and workforce unpreparedness, also slow down the process of AI integration and sustainable implementation (Zerfass et al., 2020).

The psychological and cultural factors are significant contributors to AI adoption, and skills unrest can be even more important than the fear of job loss (Yam et al., 2023; Willcocks, 2020). To align AI implementation with organizational objectives, it is necessary to have transformational leadership, employee involvement, and extensive training (Cramarenco et al., 2023). However, there is a lack of empirical evidence on resistance management and the leadership influence on AI implementation in QMS that is presented in the literature. Adoption is influenced by the technical, organizational, and human factors such as the perceptions of trust, control, tool customization, interface simplicity, and support, which impact the positive results (Chew and Achananuparp, 2022; Bankins et al., 2024). The use of AI enhances the efficiency of processes, decision-making, and quality monitoring, but such issues as a lack of data and the inapplicability of models remain (Cioffi et al., 2020; Chen and See, 2020; Carvalho and Lima, 2022). Trust, transparency, user acceptance, organizational culture, ethical considerations, and perceived benefits are the key factors of long-term effectiveness (Jermutus et al., 2022; Middleton et al., 2022; Georgopoulos et al., 2023). The majority of research is conducted in controlled or short-term settings, which have not been combined across sectors, empirically validated, human and ethical operationalized, or cost-effective in the long run. Further studies are necessary to use holistic, integrated systems to facilitate effective, ethical, and scalable implementation of AI-based QMS.

The hypotheses that were proposed to test the relationships in the study are as follows:

Direct Effects

H1: The cost-effectiveness of AI implementation will positively depend on ethical implications of AI.

H2: The issues of AI integration will have a negative effect on the cost-effectiveness of AI implementation.

H3: The issues related to AI integration will have an adverse effect on the efficiency of AI-based QMS.

H4: AI integration scalability will have a positive impact on the cost-effectiveness of AI implementation.

H5: When implementing AI, the cost-effectiveness of AI-based QMS will positively affect its effectiveness.

Mediated (Indirect) Effects

H6: The implementation of AI will be a mediator of the relationship between the ethical implications and the effectiveness of AI-driven QMS.

H7: Cost- effectiveness of the implementation of AI will mediate the relationship between AI integration challenges and effectiveness of AI-driven QMS.

H8: The implementation of AI will be cost-effective, and it will mediate a relationship between the scalability of AI integration and the effectiveness of AI-driven QMS.

Theoretical Foundation

The research is based on the Sociotechnical Systems Theory (STS), according to which we can only be successful in implementing technology into the organizational environment by maximizing both the social and technical systems clearly. Besides, the research is influenced by the Technology Acceptance Model (TAM), which determines the usefulness and ease of use as important variables that will determine the technology acceptance. Lastly, other elements of Cost-Effectiveness are mediated by the conceptual models of Strategic Management Theories and Organizational Efficiency in the following sense that efficacy created as a result of technological investments is a form of intermediary between capability and performance

METHODOLOGY

The quantitative and cross-sectional survey method was used to conduct the study in the direction of some hypotheses. The research was aimed at professional, managerial and technical managers of AI-based QMS in the manufacturing, service, healthcare and IT sectors. This population is sampled using convenient sampling of the individuals and snowball sampling. At least 300 individuals were consulted in this study, which was in accordance with the recommendations of SEM and multiple regression research. The study employed a structured online survey in the collection of data that was distributed through Google Forms and enabled the respondents to respond to the poll anonymously and whenever it was convenient to them. The questionnaire included the closed-ended items that were operationalized using the validated dimensions and were based on the previous studies in peer-reviewed articles.

The questionnaire questions were designed by modifying validated measurements that are available in literature. Even though some of the original instruments that were determined in previous studies have a massive number of items, the previous literature proves that scale reduction is a legitimate practice done in an orderly manner because shorter instruments may still possess strong psychometric characteristics. (Famodu et al., 2018) used a reduced version of the Pittsburgh Sleep Quality Index (19 to 13 items) with a high degree of reliability, whereas (Vold et al., 2020) confirmed the use of three items of the Fatigue Severity Scale. Based on this precedent, the most representative items were taken in each construct in this study. The questionnaire was tested on 70 participants to ensure that it was clear. The ultimate structure of the tool was comprised of 48 items that were to address the contents. In this study, reliability was measured in terms of Cronbachs Alpha, Composite Reliability (CR) and outer loading of indicators. The construct validity was studied in this research, and it was evaluated using convergent and discriminant validity. Average Variance Extracted (AVE) was used to confirm Convergent Validity. Both, Fornell-Larcker and Heterotrait-Monotrait Ratio (HTMT) were used to compute Discriminant Validity.

Analysis was done using a combination of SPSS and R Studio (with Seminr package). Preliminary data screening and descriptive statistics were done in SPSS. In order to test the mediating effect of Cost-Effectiveness, bootstrapping was carried out with 500 resamples, structural model was analyzed with the bootstrapping procedures with 500 resamples to obtain the path coefficients, t-statistics and p-values. The questionnaire was designed in such a way that no personal identifiable information (PII) such as name, email address, phone number, etc. was acquired; thus, it was created to safeguard the individuality and the information of the respondents.

RESULTS AND ANALYSIS

Descriptive statistics were determined in order to determine general perceptions about the key constructs in the model. The majority of items showed moderately high mean scores (3.2 to 3.9), indicating more positive attitudes.

The bootstrapped indicator loadings indicated that all the items load significantly on their latent constructs. In other words, all the standardized loadings were greater than the recommended lower level of 0.50 that is, 0.545 (ETTR1) to 0.848 (ETPR1). Moreover, the t-statistics of all loadings were bootstrapped and had values above 1.96 and the 95 percent CIs were not including zero indicating that all the loadings are significant at $p < 0.05$. All these results provide the definite conclusion of indicator reliability and reflective measurement model structure (Hair et al., 2021). The measurement items are the codes of the variables used in the analysis (e.g., DA1, ET3).

Interrelations between Cronbach Alpha (alpha), Composite Reliability (rhoC) and rhoA were used to measure the level of internal consistency reliability. All the constructs had values ranging between 0.70 and 0.98 on all three measures, which is satisfactory (Hair et al., 2021). Specifically, the Cronbach Alpha values were between (0.739) Challenges} to {(0.836) Cost-Effectiveness} which is a somewhat typical manner of expressing that there was an acceptable, and good outcome on internal consistency. Composite reliability (rho C) was 0.830 and 0.890 and the rhoA value was 0.771 and 0.853 and it once again shows that the items were consistent with the respective latent constructs.

Convergent Validity (AVE): To test the convergence validity, the Average Variance Extracted (AVE) of the individual latent variables were tested. The thing is that AVE value greater than 0.50 indicates that a construct can explain more than a half of the variations of its indicators (Hair et al., 2021). All the AVEs met this requirement with all the values lying in the range of 0.527 (Effectiveness) and 0.670 (Cost-Effectiveness) as indicated in Annexure C. These results provide assurance to the fact that convergent validity has been met in the measurement model in all the constructs.

Discriminant Validity

The Fornell Larcker brings to an end that when the square root of the Extracted (AVE) of each construct is stronger than the relationship between the construct and all other latent constructs then the discriminant validity is achieved. The diagonal values (square roots of AVEs) are never less than the inter-construct correlations they have either in the row or column sectors as indicated in Annexure D. These results are also added to the fact that the discriminant validity is effectively attained in the measurement model. The HTMT ratio of correlations was also evaluated based on the suggested approach suggested by (Roemer et al., 2021). In support of the analysis, bootstrapped 95% confidence intervals (500 subsamples) were also calculated. The values of all the HTMT, as shown in Annexure D, were within the range of 0.805 to 0.888 and not higher than the conservative value of 0.90 indicating that each construct is empirically different than the other. These results prove that the measure model possessed all the constructs that generated discriminant validity.

Structural Model

It was tested as a test of direct relationship between hypothesized latent constructs. Each of the five direct paths were statistically significant at the level of 0.05. The t-values of both the paths were higher than the critical value of 1.96 and the 95 percent interval did not include the value of zero either, indicating that the relationships were significant. Annexure B provides the R-Plot. In its turn, these results are inclined to confirm all hypothesized structural relationships and demonstrate that all of the suggested direct relationships in the model are empirically determined. The summary of hypothesis testing is displayed in annexure E.

Ethics → Cost-Effectiveness (b = 0.385, t = 7.749, 95 percent CI [0.293, 0.491]). The cost-effectiveness was impacted by the employment of ethics effectively and positively as well, which means that the influence of ethics may be effective in ensuring that the AI-driven system will as efficient as possible. Challenges → Cost-Effectiveness (b = 0.250, t = 5.614, 95% CI [0.157, 0.328]). Issues such as workforce readiness and technical illiteracy had a moderate impact on cost outcomes, therefore requiring control over such issues in order to attain economic performance.

Scalability → Cost-Effectiveness (b = 0.289, t = 5.212, 95% CI [0.182, 0.395]). The aspect of scalability was moderate and significant and therefore, when more of the AI integration was used and of a scaled nature, then there was improvement in cost performance. Challenges → Effectiveness (b = 0.371, t = 6.342, 95% CI [0.247, 0.472]). The effectiveness of the systems was also directly influenced by challenges that had to be dealt with in order to reach their optimal performance. Cost-Effectiveness → Effectiveness (b = 0.469, t = 8.796, 95% CI [0.364, 0.574]). Predicting success to the AI-driven QMS was in high support of the mediating role of cost-effectiveness and a central role in the model.

These findings are likely to confirm all the hypothesized structural relationships and demonstrate that all the suggested direct relationships in the model are confirmed empirically. To quantify the total effect of construct on the other both direct and indirect effects were taken into account with the assistance of bootstrapped total effects (500 subsamples). The total effects are all statistically significant at the 95 percent confidence levels with the confidence intervals not intersecting with zero.

Mediation Analysis: To use the data to test the mediating position of Cost-Effectiveness in the associations among the independent variables and the dependent variable, bootstrapped indirect effects were computed with 500 resamples. The findings indicate that Cost-Effectiveness plays a significant mediating role in all the three hypothesized relationships:

H6 was accepted, and it means that the impact of Ethical Implications on the Effectiveness of AI-driven QMS is mediated by Cost-Effectiveness (indirect effect = 0.181, 95% CI [0.118, 0.243]). H7 was also confirmed that it shows that the Effectiveness is affected due to Integration Challenges both directly and indirectly via Cost-Effectiveness. The overall impact was 0.488, the indirect part of which was 0.117 (calculated as 0.488 − 0.371). H8 was also supported, which means that Scalability has an indirect impact on Effectiveness via Cost-Effectiveness (indirect effect = 0.135, 95% CI [0.088, 0.191]).

DISCUSSION AND CONCLUSION

Discussion

Direct effects refer to the direct association between construct without the intermediary variables. To begin with, the Effectiveness of AI-driven QMS is not statistically affected by the Ethical Considerations, which proves that Ethical Considerations have the effect on Cost-Effectiveness only. The effect of this on Cost-Effectiveness is significant, positive (b = 0.385, t = 7.749, 95% CI [0.293, 0.491], $p < 0.001$). These findings are consistent with Abdullah and Fakieh (2020) who pointed out that adoption of AI in organizations must be grounded on trust, transparency, and fairness as they are significant to efficiency in organizations and acceptance by the users of the AI. Secondly, AI Integration and Effectiveness of AI-Driven QMS do not play a major role in the structural model under test, the relationship was only indirect and fully mediated by Cost-Effectiveness. Scalability had the most positive and significant impact on Cost-Effectiveness (b = 0.289, t = 5.212, 95 CI percent [0.182, 0.395], $p < 0.001$) which in turn has a positive impact on Effectiveness. Scalability has an indirect effect of (b indirect = 0.135). The results correspond to Baryannis et al. (2019), who asserted that scalable AI systems enable the flexibility of responding to the dynamic workload and environment and reduce the unit cost of operation. Thirdly, the results indicate the unexpected relation of integration challenges on Effectiveness, that there is a positive statistically significant direct correlation (0.371, t = 6.342, 95% CI [0.247, 0.472], $p < 0.001$). It implies that active measures to introduce the integration issues to the case in question (technical illiteracy, fear of AI, cultural resistance, and workforce readiness) can help the organizations to make AI-implemented QMS more efficient to a significant degree. The favorable indirect effect was great (b indirect = 0.117, t = 5.614, 95 percent CI [0.394, 0.583]) which means that the integration issues also indirectly contribute to the effectiveness by increasing the cost-effectiveness. Finally, the results indicated there was an extreme and significant direct connection between the Cost-Effectiveness and the Effectiveness of AI-Driven QMS (0.469, t = 8.796, 95 percent CI [0.364, 0.574], $p < 0.001$). This confirms the fact that establishing AI-based quality management programs in a cost-efficient manner, one would maximize its impacts on the performance of the whole system.

Mediated Effects

First, Ethical Considerations (b = 0.385) have a great impact on Cost-Effectiveness and, in turn, a strong impact on Effectiveness (b = 0.469). The significance of the indirect effect (b indirect = 0.181) and the non-occurrence of the direct effect show that the finding is significant and the effect is fully mediated. This means that the AI-QMS performance can be enhanced in every respect by considering ethical concerns, which makes it cost effective.

Second, the challenges on the Integration of AI have a positive and significant influence on the Cost-Effectiveness ($b = 0.250$). The indirect effect (b indirect = 0.117, 95% CI [0.064, 0.175]) however, is significant, as Effectiveness ($b = 0.371$) is also significant, so this is partial mediation. This means that even though it can contribute significantly to the effectiveness directly to the issue of integration, it can indirectly contribute to it too by making it more cost-effective. Finally, the scalability has a positive and significant influence on Cost-Effectiveness (95% CI [0.182, 0.395], $p < 0.001$) that has a significant effect on Effectiveness as well. It is significant and the fact that the effect is not direct is a good confirmation that there is full mediation. It means that scalability increases effectiveness in its whole due to its impact on cost-efficiency.

Theoretical Contributions

The results are in line with the STS viewpoint, which focuses on the interdependence of the social and technical subsystems to produce organizational effectiveness. The combination of social (ethics), technical (scalability), and organizational (integration challenges) factors leads to optimal QMS results in an empirical way. Also, the cost-effectiveness becomes a mediating variable between social-technical alignment and performance outcomes, which introduces an economic aspect to the standard STS model. Such constructs as ethics, scalability, and integration issues have both direct and indirect impacts on adoption outcomes by being related to cost-effectiveness and generalizing TAM to AI-driven QMS settings. This paper narrows down TAM by defining cost-effectiveness as an objective economic performance instead of a subjective concept, facilitating the gap between psychology-oriented TAM and long-term organizational performance. The findings indicate that the successful implementation of AI-QMS is not only based on the quality of processes and products but also on the economic feasibility, with ethics, scalability, and integration having a positive impact on operations and strategy. Finally, AI-QMS should be sustainable in terms of technical capacity, ethical regulation, and economic feasibility.

Practical Implications

The ethical issues have a significant and positive impact on the cost-effectiveness, which, in turn, promotes the overall effectiveness, as it will improve costs and long-term outputs of AI-QMS. Scalability is also positively related to cost-effectiveness, which completely mediates its effect on overall effectiveness because scaling operations, markets, and technology do not decrease performance but lower unit costs, downtime, and resource consumption. The challenges of integration that are addressed with the help of training, communication, executive sponsorship, and gradual adoption have a positive impact on cost-effectiveness and overall effectiveness. The cost-effectiveness proves to be the strongest predictor of long-term QMS results, which can be measured through cost per AI inference, hours saved, and resources optimized, and such savings are reinvented to strengthen additional efficiency and organizational changes

Conclusion

The paper will discuss the functions of ethics, scalability, and integration issues in AI-QMS, with the mediating role of cost-effectiveness serving as the intermediary between the organization and effectiveness. Results indicate that ethics and scalability have the full impact on effectiveness in the form of cost-effectiveness, whereas integration issues have both direct and indirect impacts. Ethical behaviors (transparency, fairness, responsible AI) and scalable system architectures increase operations primarily by increasing cost-efficiency, but resolving integration problems leads to better performance than cost savings. The cost-effectiveness becomes one of the key strategic instruments that would translate the ethical governance and scalability into the improved AI-QMS results where there has to be a compromise between the financial efficiency and the operational interventions. In reality, ethical frameworks, scalable infrastructures, and integration management should be strategically invested by organizations to attain sustainable and cost-effective AI-QMS. Theoretically, the research makes its contribution to the AI-QMS literature by proving the mediation of cost-effectiveness empirically, the dependence of scalability on resource efficiency, and the two-sidedness of integration issues in a cross-industry view. To managers, the research recommends that they emphasize on cost effective practices that can facilitate ethical artificial intelligence, scalable design, and lower integration barriers to optimize organizational performance.

The findings at the policy level imply that the coordinated regulation frameworks are required that balances ethical protection, technological scalability, and economic feasibility. It is recommended that policymakers consider cost-efficiency to the ethical AI guidelines, encourage the development of scalable and resource-efficient AI solutions and radical action to execute dual policy approaches, which entails financial incentives and operational support. Investments in upskilling people and cross-industry cooperation are also significant in minimizing systemic barriers and responsible and large-scale implementation of AI-based quality systems.

The paper will be restricted to three high-impact areas, manufacturing, healthcare and IT industries. The reason behind selecting these industries was due to the variation in the patterns of operation, regulatory requirements, and focus on ethics. The cross-sectional research design does not allow the interpretation of causality and does not indicate the dynamics of changes in the effectiveness of AI-QMS over time. Self-reported data may be biased, even with the controls of statistics. The sample was also selected mostly on the basis of organizations that already have experience with QMS and AI, which could not allow generalizing it to less mature or publicly-based organizations. Moreover, the mediation analysis did not analyze the other potentially relevant mediators like employee trust, AI literacy or system interoperability. The accelerated technological advancement in the AI and QMS tools sphere will also show that the relationships in question can also be different as the technologies and regulatory conditions are shifting.

Considering these shortcomings, subsequent studies are advised to use longitudinal research designs in investigating the mediating effect of cost-effectiveness as AI-QMS become mature. Industry-specific studies might also be useful in further explaining the significance of industry characteristics in the strength and nature of these relationships. Qualitative or mixed methods would be more contextual in terms of the role of ethics, scalability and challenges in identifying cost-effectiveness and effectiveness in practice. Such an expansion of mediation models to incorporate organizational culture, employee trust, and technological readiness would explain the AI-QMS performance in a more comprehensive manner. Lastly, the international comparative studies might be used to comprehend the place of policy, cultural, and infrastructural variations in the results of AI-based quality management efforts.

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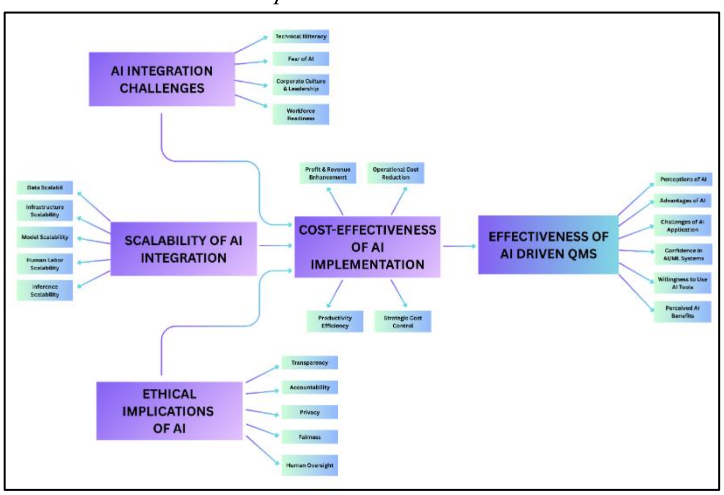
ANNEXURES

Annexure A: Conceptual Model

Figure A1: Conceptual Model of the Study

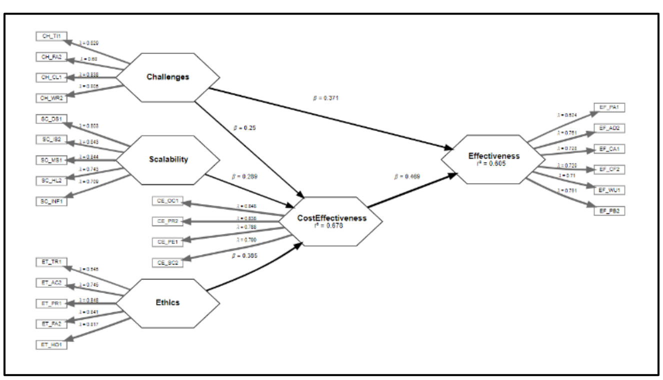
Source: Author's conceptualization



Annexure B: Structural Model

Figure B1: Structural Model (Bootstrapped PLS-SEM Results)

Source: Author's computation using R (Seminr)



Annexure C: Measurement Model Results

Table C1: Internal Consistency Reliability and Convergent Validity

Source: Author's Computation

Construct	Cronbach's Alpha (α)	Composite Reliability (ρC)	Average Variance Extracted (AVE)	rhoA
Ethics	0.821	0.875	0.589	0.853
Challenges	0.739	0.83	0.552	0.771
Scalability	0.804	0.866	0.565	0.811
Cost-Effectiveness	0.836	0.89	0.67	0.838
Effectiveness	0.82	0.869	0.527	0.833

Annexure D: Discriminant Validity

Table D1: Fornell–Larcker Criterion

Source: Author's computation

	Ethics	Challenges	Scalability	Cost Effectiveness	Effectiveness
Ethics	**0.768**	0.676	0.692	0.753	0.69
Challenges	0.676	**0.743**	0.697	0.711	0.705
Scalability	0.692	0.697	**0.752**	0.729	0.677
Cost Effectiveness	0.753	0.711	0.729	**0.818**	0.733
Effectiveness	0.69	0.705	0.677	0.733	**0.726**

Table D2: HTMT Ratios

Source: Author's computation

Constructs	Ethics	Challenges	Scalability	Cost Effectiveness	Effectiveness
Ethics	—				
Challenges	0.805	—			
Scalability	0.835	0.872	—		
Cost Effectiveness	0.888	0.828	0.888	—	
Effectiveness	0.818	0.883	0.829	0.867	—

Annexure E: Hypothesis Testing

Table E1: Hypothesis Testing Summary

Source: Author's computation

Hypothesis	Statement	Status	Evidence
H1	The cost-effectiveness of AI implementation will positively depend on ethical implications of AI.	**Supported**	β = 0.385, t = 7.749, p < 0.001
H2	The issues of AI integration will have a negative effect on the cost-effectiveness of AI implementation.	**Not Supported**	β = 0.250, t = 5.614, p < 0.001
H3	The issues related to AI integration will have an adverse effect on the efficiency of AI-based QMS.	**Not Supported**	β = 0.371, t = 6.342, p < 0.001
H4	AI integration scalability will have a positive impact on the cost-effectiveness of AI implementation.	**Supported**	β = 0.289, t = 5.212, p < 0.001
H5	When implementing AI, the cost-effectiveness of AI-based QMS will positively affect its effectiveness.	**Supported**	β = 0.469, t = 8.796, p < 0.001
H6	The implementation of AI will be a mediator of the relationship between the ethical implications and the effectiveness of AI-driven QMS.	**Supported**	Indirect β = 0.181, t = 5.899, p < 0.001
H7	Cost- effectiveness of the implementation of AI will mediate the relationship between AI integration challenges and effectiveness of AI-driven QMS.	**Supported**	Indirect β = 0.117, t = 4.660, p < 0.001
H8	The implementation of AI will be cost-effective, and it will mediate a relationship between the scalability of AI integration and the effectiveness of AI-driven QMS.	**Supported**	Indirect β = 0.135, t = 4.667, p < 0.001