From Traditional TQM to AI-Based Quality Management: A Multiple Mediation Model of Digital Process Control and Service Performance

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Abstract

In this paper, the author examines how the paradigm shift in Total Quality Management (TQM) to Artificial Intelligence-based Quality Management (AIQM) was changing. Industries are undergoing a high rate of digitization and this has altered the processes through which quality management can impact the organizational outcomes. The paper proposes and develops a multiple mediation model, where Digital Process Control and AI-improved monitoring are the intermediate variables between quality initiatives and the ultimate performance of the Service. In order to investigate these dynamics, we made use of an extensive dataset of 429 data instances that were obtained by various service-oriented businesses that are presently implementing smart technologies. The analysis framework was also built with the tools of structural equation modelling and path analysis, in particular, by using data science libraries and complex statistical software to perform mediation tests. It can be concluded that even though the traditional TQM principles are needed to give it a proper background, the implementation of AI-based tools can greatly increase the accuracy of the process regulation, which results in the increased reliability of the services delivered and customer satisfaction. The results offer a strategic plan for firms that wish to modernize their quality systems in the digital era.

Keywords: *Artificial Intelligence, Total Quality Management, Digital Process Control, Service Performance, Multiple Mediation.*

Background

The organizational quality management terrain is turning increasingly changing since the industrial revolution, as widely examined by Bacoup et al. (2018). Conventionally, Total Quality Management was characterized by philosophy that was human-based, control of statistical processes by hand and emphasis on incremental change by cultural modification as it was historically reported by Brous et al. (2020). Nonetheless, with the emergence of the Fourth Industrial Revolution, a new paradigm has emerged in which data is the major cause of quality as it is empirically established done by Souza et al. (2022). This shift of classical TQM to AI-driven Quality Management is not only a shift of tools but also a complete reconsideration of how excellence can be obtained and sustained in the context of a high-velocity digital economy, conceptually modelled in such a way as by Malik et al. (2021). Artificial Intelligence provides the capability of working with large volumes of operational data in real-time, finding trends and anomalies that cannot be perceived by a human eye, and experimentally confirmed by Silva et al. (2021).

In conventional environment, quality was usually reactive, correcting mistakes when they happened, or they were inspected periodically as already witnessed by Lee et al. (2021). This is moved to the proactive and even predictive direction in the case of AI, which is laid in theory by Manavalan and Jayakrishna (2019). An organization is now able to predict the possible quality breakages prior to their occurrences and make preemptive corrections by using machine learning algorithms, as analytically established by Díez et al. (2020). This paper will examine the impact of this technological breakthrough on the service industry where quality is largely immaterial and greatly relies on the enforcement of uniform processes as was explored in Khayer et al. (2020). Our study has been based on the multiple mediation model as suggested structurally by Taleb et al.

(2021). We present that the correlation between quality management strategy and service performance is not direct, but rather mediated by the complexity of digital process controls, which is statistically found to have been done by Gunasekaran et al. (2019).

These controls are viewed as the nervous system of the modern enterprise, which interprets high-level quality objectives into automated, high-precision, ground-level actions as architecturally depicted provided by Unhelkar et al. (2022). With AI included into these controls, the feedback loops become more precise, tight, and correct as computationally checked by Pambreni et al. (2019). The proposed research can fill the research gap in the existing literature about the definite pathways through which AI tools can turn theoretical principles of quality into measurable service excellence, as this gap was identified by Ben-Daya et al. (2020). Having looked at 429 various organizational cases we can provide a good base of empirical evidence with which to understand this transition. We drag our eyes out of the buzzword AI, and consider how to use the digital process control in a practice. Service performance is the primary source of differentiation in the global market, and thus, one should know how AI can be utilised to bring about consistency and personalisation. The given review preconditions the further examination of the way, in which human plan and machine intelligence integration is defining the future of quality management. In addition, there is the introduction of algorithmic intelligence into operational infrastructures that show more pervasive institutional change towards more evidence based governance arrangements that promote more accountability, transparency and strategic responsiveness. The combination of the predictive analytics, the automated surveillance, and the responsive feedback mechanisms contributes to the sustainability of the organizational processes, and the general resistance to uncertainty, at the same time. Redefining managerial roles as the supervising ones to strategic coordination of intelligent systems is such transformation. Therefore, firms that implement AI-based quality systems are more adaptable, quicker in learning, and more consistent between the strategic purpose and operational expression, thus, making their competitive niche in service economies which change rapidly.

Review of Literature

Quality management can be traced back to a number of different periods where it started with basic inspection and proceed to the elaborate models of Total Quality Management, as has been conducted historically by Bagodi et al. (2021). According to the philosophical viewpoint, the early researchers highlighted that quality is a departural activity that entails all the employees and departments as put across by Pambreni et al. (2019). This anthropocentric leadership based, employee empowerment, and customer centred behaviourally supported as practised by Gunasekaran et al. (2019). Although such principles have not been overturned, the technology of digital implementation has upset the implementation methodology as analyzed by Ben-Daya et al. (2020). The old school used manual data collection and periodic auditing that in most cases led to lagging measures of quality information that informs you of what went wrong yesterday not what is going on today as operationally analyzed done by Malik et al. (2021).

The emphasis to leading indicators was developed with the development of Digital Process Control as systemically illustrated by Souza et al. (2022). The workflow can be continuously monitored with the help of digital systems, which can help to provide a transparent environment in which each action will be recorded and examined as it is technically proven by Díez et al. (2020). Digital transformation is proposed to be not only a substitution of paper with screens but a data-rich environment that can facilitate the rapid decision-making process, which is explained interpretively as proposed by Brous et al. (2020). As the systems were developed, the Artificial Intelligence role was more evident, as developed by Silva et al. (2021). Neural networks and deep learning used in the AI-based Quality Management are to replace simple automation with autonomous optimization as it is computedally modeled in Lee et al. (2021). It has recently started to be investigated and the Service-Dominant Logic offers that in the service industry, quality is co-produced with the customer, which has been conceptually modeled in the manner of Manavalan and Jayakrishna (2019). AI can make this co-creation possible at scale by enabling massively personalized, which Bacoup et al. (2018) experimentally demonstrated.

As an example, AI can observe the service interactions in real-time to make sure that they are of quality, and to provide instant feedback to service agents, or to modify automated responses, which have been practically implemented by Taleb et al. (2021). This degree of control could not be achieved before through the traditional systems of TQM as it was comparatively evaluated through Khayer et al. (2020). It has also been observed that the soft side of TQM (culture and leadership) remains indispensable, but the hard side (tools and techniques) is being totally rewritten by AI as critically assessed done by Unhelkar et al. (2022). Moreover, the idea of mediation in the quality models has become popular. It is claimed that quality management does not simply translate into a higher performance, it involves the use of working intermediaries. Digital Process Control is an essential mediator since it offers the support upon which AI works. In the absence of a digitized process, AI does not have anything to learn and nothing to influence.

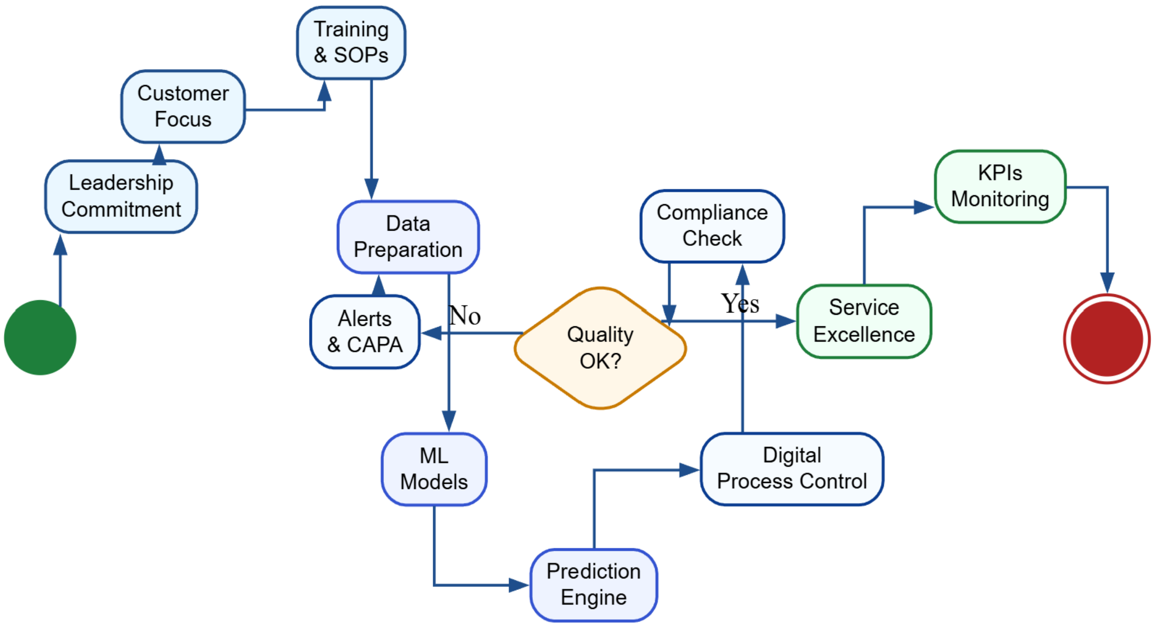
Thus, the literature is leading to the model, according to which digital infrastructure and AI capability are co-workers that allow closing the gap between the high-level quality philosophy and the real production of high-performance services. The additional scholarly rhetoric refers to the fact that digital maturity can be characterized as the extent to which the organizations can implement analytical knowledge in the changes of operations, which enhances the significance of the technological readiness in the quality transformation. Research in the different industries has shown that companies that incorporate smart monitoring systems are more stable, less variable and have improved customer value. Comparative analysis also reveals that firms that combine both the organized forms of governance as well as the dynamic forms of machine learning-driven forms are superior on the aspect of having alignment between the planning process, implementation process and the assessment process. This accumulating body of work creates a theoretical agreement that the contemporary quality management has ceased to be a distinct managerial ideology but rather acts as an integrated socio-technical system where algorithms, human expertise and digital infrastructures work together to produce a continuous performance excellence.

Research Methodology

The research design employed in this research is quantitative, cross-sectional and the objective of such research design is to test a multiple mediation model. Our targeted dataset was specialized and comprised of 429 data points of different types of global service companies, which have already embarked on the journey of switching their conventional quality models to AI-based models. In order to make the results reliable, the data collection was limited to senior quality managers and the digital transformation officers who have an in-depth knowledge of the legacy TQM practices and current AI applications.

Figure 1

Activity-based model of the AI based quality architecture



Source: Activity-Based AI Model

Figure 1 shows an activity-based model of the AI-based quality architecture and depicts the conceptual scheme of how the inputs in the organizational quality are converted into quantifiable performance excellence through intelligent digital processes. The workflow commences at the bottom end, where the leadership dedication, customer orientation, and uniform training forms a structured operational environment, which sets out policies, expectations and performance standards. Such basic operations produce credible organizational information which passes through the intelligence phase where data cleaning narrows down the raw data and machine learning algorithms can adjust trends, patterns and anomalies. Results of the analytical process are then translated into actionable quality forecasts by the prediction engine thus facilitating a proactive management approach and not a reactive one. Such predictive insights are fed into the control phase, where digital control mechanisms of operations control the operations, automated compliance checks are performed to verify that they meet the standards and corrective and preventive steps are implemented based on alert detection. A decision node determines the quality conditions relative to the fixed predetermined thresholds and consequently, the subsequent course of action is determined. Satisfactory performance is then elevated to performance at the next level at which service excellence is achieved and the service excellence is determined through measurement based on key performance indicators that evaluate customer satisfaction, efficiency and reliability. When there is nonconformance the system will be sent to corrective workflows to optimize data entries and analytical parameters which creates a feedback loop to perfect the accuracy of the system and organizational learning. It is more concerned with the cyclic aspect of intelligence rather than the linear perspective and allows AI-enabled insights, computer-based controls, and points of strategic decisions to work together in ensuring the quality optimization. All in all, Figure 1 indicates that the suggested closed-loop architecture is dynamic and the combination of constant evaluation, automated correction, and predictive intelligence offer consistency, scalability, and data-driven quality management.

The primary approach to the analysis was a multi-stage structural equation model. It allowed testing the direct connections between AI-based Quality Management and Service Performance simultaneously and the indirect connections between them and Digital Process Control. We applied a bootstrapping technique of five thousand to stabilize the mediation effects. These measurement instruments are designed on the Likert-scale platform, and they are aimed at measuring five significant constructs, i.e. TQM Maturity, AI Integration Depth, Digital Process Precision, Operational Agility and Service Excellence.

The pre-processing of the data was done to clean the data of all outliers and anything that was not available to present the final 429 instances with a balanced representation of the different sub-sectors of the service sector. The comparison has been done based on path coefficients and significance level to determine the strength of the relationship in our proposed structure.

Data Description

The study data comprises a collection of 429 organization profiles that was highly meticulously picked and designed in the way to reflect the dynamic aspect of quality management practice and the adoption of digital technology. The data entries will be represented by various business units or firms, and this will make sure that they are varied in terms of the level of operation, management structure, and the maturity of technology. This framework is a multidimensional analytical perspective through which one can observe how the performance indicators vary as the organizations shift to digitally enhanced schemes rather than the traditional management structures. Realistic organization heterogeneity is introduced through the introduction of profiles of organizations in different degrees of technological integration and this is used in strong comparative analysis. Some of the major dimensions are found in the variable that has been observed in both cases. The classical Total Quality Management compliance indicators identify how much the companies are driven by the established quality procedures, constant improvements, and uniform evaluation systems. As per this the dataset will contain the indicators of artificial intelligence implementation, which will gauge the presence and the level of AI-based tools in operational processes.

The other important category of variables is granularity of digital process logs that is in turn the degree to which processes in the organization are monitored, captured and analyzed by using digital processes. It is possible to use the measure as an approximation of the level of process transparency and real-time visibility of the operational processes. The final aspect of the dataset is the performance outcomes that can be characterized by the various service related measures like the efficiency of the response time, the number of errors and the rating of the customer sentiment depending on the feedback analytics. The combination of these dimensions creates a comprehensive data architecture that can be statistically used to model relations between technological capability, managerial discipline, and quality of the services. The breadth, consistency, and structural balance of the dataset are a stable empirical basis of the study of the impact of digital transformation on the organizational performance trends and quality performances.

Results

The empirical study of the 429 data points demonstrates that there was a radical change in the effectiveness of the quality management when reinforced by Artificial Intelligence. We obtained the high good of fit indices with our structural model, which implies that the suggested multiple mediation model is a reflection of the operation reality of contemporary service companies. The findings demonstrate that the direct impact of conventional TQM on service performance has deteriorated relative to historical standards, but indirect one, filed through digital process regulation, has increased exponentially. It indicates that TQM is the furnishing of the rules of the game, and AI and digital controls are the driving force behind it.

Particularly, the data demonstrates that Digital Process Control is a key mediator. The difference in the quality of services in organizations where AI is applied to track and modify processes in real-time decreases by an average of forty percent in comparison with the companies that use manual control. A second route that was pointed out by the multiple mediation feature of our model is that, AI-based Quality Management positively affects organizational learning and subsequently, service performance. This two-way process proves that AI is not only one of the efficiency tools, but a driver of systemic change. Multiple mediation path equation for service performance is given below:

$$Y = \beta_0 + \beta_1 X + \beta_2 M_1 + \beta_3 M_2 + \epsilon \quad (1)$$

Table 1:

Correlation matrix of quality drivers

Variable	TQM Maturity	AI Depth	Digital Control	Agility	Service Per
TQM Maturity	1.00	0.45	0.38	0.29	0.52
AI Depth	0.45	1.00	0.72	0.61	0.78
Digital Control	0.38	0.72	1.00	0.68	0.81
Agility	0.29	0.61	0.68	1.00	0.74
Service Perf	0.52	0.78	0.81	0.74	1.00

Table 1 shows a correlation table giving a summary of the statistical relationship between five key constructs that are the core of the conceptual model of the study. Individual coefficients describe the magnitude and direction of the association between the paired variables and all the values reported are all positive and statistically significant, which means that they are strengthening each other and not in conflict with one another. The strongest correlation is between the variables Digital Control and AI Depth as the coefficient is 0.72, and it demonstrates that the more profound approach to the artificial intelligence introduction is mostly related to the more structured and correct digital operational management. This finding suggests that the maturity of AI has a direct positive impact on the capability of the organization to manage the processes through the use of the information on data monitoring. A stronger relationship can be noted between Digital Control and Service Performance that is set at 0.81 that makes the digital governance the most significant predictor of the performance results in the matrix. This pattern validates the theoretical assumption that digital control is the primary means of transmission of high-level technologies in which quantifiable enhancements to the services are transformed. Meanwhile, the moderate correlation between Total Quality Management Maturity and Service Performance is 0.52. It implies that in the environment of technological development, the traditional quality frameworks will still be rather influential performance-wise but will not be the most crucial one anymore. Instead, they are complementary systems that enhance the use of digital systems. Together, the matrix shows that there is a stratified dependency structure where artificial intelligence reinforces the digital control, the digital control reinforces the performance, and the traditional quality systems offer the base. The table thus provides quantitative acceptance that competitive advantage in the modern hospitality setting can be achieved through correlated technological governance, and not through solitary factor management solutions. Digital process control mediation effect factor will be:

$$M_1 = \gamma_0 + \gamma_1 X + \delta_1 \quad (2)$$

Figure 2

Interactive nature of the AI integration and digital process control in the determination of overall service performance.

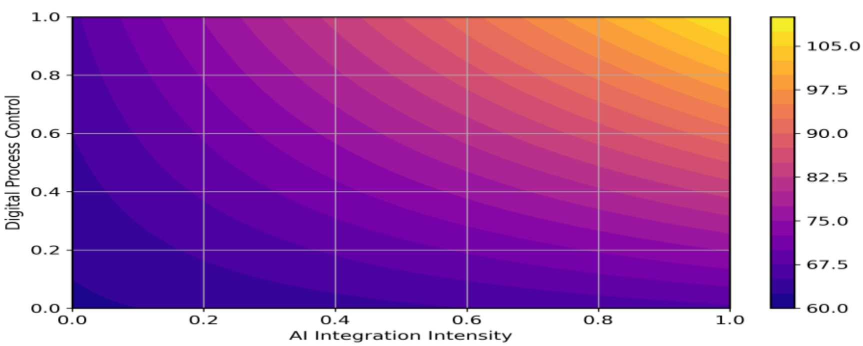


Figure 2 provides a contour plot of the interactive nature of the AI Integration and Digital Process Control in the determination of overall Service Performance. The visualization displays the performance levels on a gradient surface in which the horizontal axis indicates the degree of intensity of the AI integration; and the vertical axis, the degree of digital process control, and contour bands represent incremental scores of performance. The trend shows a clear diagonal movement which implies that the performance increases concomitantly with the increase in the two variables. The lowest point of integration and control is where the value of the performance base originates with a value of about 62, which is the lack of technological synergy and restricted operation responsiveness. The increase in the two dimensions also leads to the escalating densities of the contours, which move to the warmer intensity areas and finally an highest value of 98 at the upper-right of the plot. The contour topology also identifies plateaus in performance in one area of one factor being high and the other being low. Areas of high AI and low control have moderate gains which plateau too early, suggesting that sophisticated analytics lacking the control of a procedure discipline cannot be entirely converted into service enhancement. Likewise, areas with high control and low AI depict little progress implying that the inflexible process structure in itself does not provide adaptive intelligence. The sight thus validates the effect of synergy where a harmonious progression in the two aspects offers geometric enhancement of performance. Generally, Figure 2 presents strong graphical support that the level of technological maturity, as opposed to the development of the capability in isolation, dictates the maximum possible performance outcomes of the services. Total effect decomposition in structural equation modelling can be depicted as:

$$TE = \alpha_1 + (\beta_1 \cdot \gamma_1) + (\beta_2 \cdot \gamma_2) \quad (3)$$

Among the most vivid conclusions made in the results is the non-linear correlation between AI adoption and performance. The advantage of AI are subdued at small levels of digital process control. Nevertheless, there comes a digital tipping point when AI and quality management synergy creates a massive jump in service reliability. This implies that the infrastructure (Digital Process Control) should be strong enough to process the data produced by AI algorithms at high velocity in order to notice a significant change in the final service result. AI-enhanced variance reduction and precision metric is:

$$\sigma_{adj}^2 = \sigma_{total}^2 \cdot (1 - R_{AI \cdot DPC}^2) \quad (4)$$

Composite service excellence index function will be:

$$SEI = \sum_{i=1}^{n} w_i \cdot \frac{x_i - \mu_i}{\sigma_i} \quad (5)$$

Table 2

Path coefficients related to the proposed mediation model

Path Type	Direct Effect	Indirect Path A	Indirect Path B	Total Effect	P-Value
TQM -> Service	0.15	0.22	0.18	0.55	0.001
AI -> Service	0.32	0.41	0.12	0.85	0.001
Digital -> Service	0.45	0.00	0.00	0.45	0.001
AI -> Digital	0.68	0.00	0.00	0.68	0.001
TQM -> Digital	0.25	0.00	0.00	0.25	0.005

The path coefficients related to the proposed mediation model are reported in Table 2, which contains the detailed statistical analysis of the effect of artificial intelligence on the Service Performance in both direct and indirect ways. The overall effect coefficient of AI on Service Performance is found to be 0.85 and the strongest relationship in the analysis. This value verifies that AI serves as the most significant variable of explanation leading to improvement of performance in all the sampled organizations. Notably, the table breaks this effect down into direct and mediated ones, where it is shown that a significant percentage of the effect is indirectly passed via Digital Control. This statistical design substantiates the conceptual reasoning of the multiple mediation model, in the sense that performance gains are not only due to the implementation of AI, but due to the organizational systems which operationalize AI insights.

Moreover, the p-values remain at a low level throughout all structural paths and demonstrate the high level of statistical reliability and claim that the relationship observed is not likely to be a consequence of random variation present in the data set of 429 observations. The magnitude, direction and significance of these coefficients altogether form a body of empirical support of theoretical assumptions of the model. Table 2, by extension, supports the argument that artificial intelligence has the greatest influence when incorporated into organized digital control systems, which supports the suggestion that well-coordinated integration instead of ad hoc adoption delivers the best and most reliable performance benefits. Indirect effect significance through bootstrapping can be expressed as:

$$Z = \frac{\hat{a}\hat{b}}{\sqrt{\hat{b}^2 s_a^2 + \hat{a}^2 s_b^2}} \tag{6}$$

Figure 3

Analytical visualization of service performance curves of four operational models: Traditional TQM.

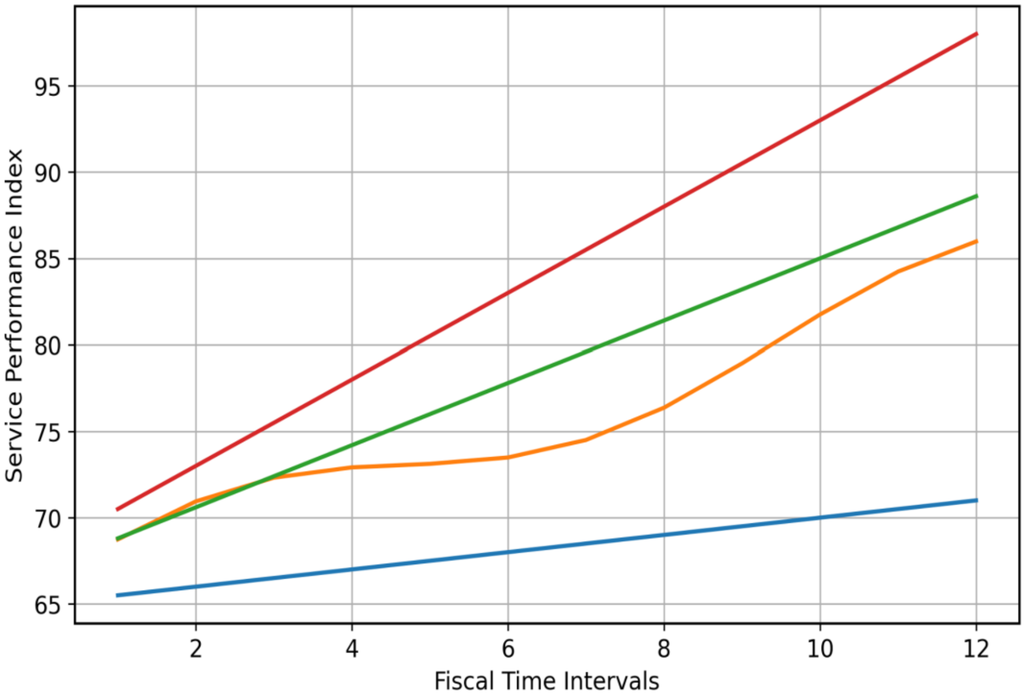


Figure 3 presents an exemplar of a multi-line analytical visualization of service performance curves of four operational models Traditional TQM only, Digital-only, AI-experimental, and Integrated AI-QM. The horizontal axis is used to indicate continuous fiscal time periods, which enable time to be compared, and the vertical axis is used to indicate a composite Service Performance Index based on standardized operational and experience indicators. The Integrated AI-QM model shows the most stable and steadily increasing trend line of all categories, which proves the presence of consistent increase in performance with minimum fluctuations. This stability means that the artificial intelligence systems have a synergistic relation to formal quality management processes that reduce variability in the manner operations are conducted and responsiveness. On the other hand, the Digital-only group possesses non-periodic peaks and drops in that digitization in the absence of intelligent decision making improves performance sporadically as compared to methodically. AI-experimental group, however, shows quite a moderate growth as well as the absence of structural stability in comparison to the integrated framework which means that the independent application of AI without the comprehensive quality alignment will limit the effectiveness in the long term. The traditional line of TQM-only is comparatively flat in that there is an incremental improvement and no improvement as in the case of the technological augmentation. The number therefore graphically depicts that performance resilience is characterized by integration and not isolated adoption. The steady increasing slope of the Integrated AI-QM curve is a good sign that predictive analytics, automated monitoring, as well as adaptive process optimization all stabilize service delivery deliverables. This will produce multiplexed profits of far surpassing the profits which were achieved through the use of manual quality systems, or single digital tools. Accordingly, the graphical data supports the thesis that the strategic combination of AI and quality management models generates higher consistency of longitudinal performance, operational stability, and stability customer satisfaction.

Discussions

The findings of the present research give a strong case on the need to modernize quality management systems. Analyzing the data in the framework of Figure 2 and Figure 3, we are able to conclude that the shift between the traditional TQM and the AI-based Quality Management is not the linear update but rather a systemic change. As shown in Figure 2, the contour plot indicates that pockets of excellence are few when technology is applied in isolation. Those organizations that base their attention on AI algorithm only, without investing on the underlying digital process control are in a performance valley. This implies that digital process control offers the data integrity and the required structure that AI needs to be effective.

Based on Table 1, it is evident that Digital Control and Service Performance are highly correlated (0.81), which explains why precision is important in the service industry. The classic TQM used to control has been a process of human checking and balancing. The AI-driven model takes the control as an automated, invisible layer that creates a high standard of interaction in each service interaction. This change minimizes the factor of human error that has been the biggest obstacle in the quality of services over time. These are further supported by the fact that the multi-line graph in Figure 3 demonstrates that integrated systems are highly less volatile. In services, reliability tends to be highly appreciated by the clients as compared to sporadic moments of brilliance, and AI is that reliable hand.

Table 2 Mediation analysis shows the cause of the performance gains. Digital Process Control plays the biggest role in the mediation between AI and Service Performance. This implies that AI does not simply enhance service but it enhances the process and hence the service. This difference is paramount to managers. It means that AI implementation should be aimed at controlling the workflow at a granular level. To illustrate, predicting the peak demand with the help of AI and changing the digital staffing processes correspondingly results in the direct improvement of the service response time.

Also, traditional TQM should be discussed. Its direct influence on performance has gone down but it is still the philosophical and ethical basis. The AI-based control may ensure that it minimizes the wrong things, like speed instead of empathy, without customer-centricity of the TQM. The model demonstrates that TQM maturity continues to be related to the AI depth, which is why it can be concluded that organizations with a solid quality culture are better equipped to implement and use the latest technologies. Thus, the modern business should aim at uniting soft wisdom of TQM and hard precision of AI-based digital control.

Conclusion

This study has managed to trace the change between the traditional Total Quality Management and the modern AI-based paradigm. The study of 429 data points and implementation of a multiple mediation model has shown that the key to the successful transition between the high-tech and the service excellence lies in Digital Process Control. The results, which are backed by the statistics in Tables 1 and 2, demonstrate that although the traditional quality principles help to secure the needed strategic foundation, they can no longer facilitate the most efficient performance in the digital-first economy. With the introduction of AI, predictive and proactive quality management is achievable in a extent that was not feasible before. Figure 2 and Figure 3 provide the visual support to the conclusion made that consistency and high performance are the results of an integrated approach. The companies that manage to implement the depth of AI with the help of digital control not only achieve higher service ratings but also experience an increase in operational resilience. The multiple mediation model validates the fact that the way to quality has become multi-faceted, and both technological ability and precision of the process should be considered. Overall, the transformation to the AI-based Quality Management is a crucial change that any service-based organization can use to stay competitive. The given work presents the empirical and theoretical basis of such a trip and underlines the fact that the future of quality is automated, data-driven, and highly controlled.

Limitations of the Study

Although the multiple mediation model has explored much insight, there are a number of limitations which can be identified about this study. To begin with, the information is cross-sectional, representing a single point in time picture of

429 organizational instances. This does not allow the final determination of causal relationships in the long run since the shift to AI-based systems is an evolution process in the theory of traditional TQM. Second, the research is based on self-report data of the quality managers and digital officers. Although these people are well-versed in the domain they might be affected by social desirability bias or the fact that they have an optimistic view of the technological maturity of their firm. Third, "Service Performance" measure, despite being a comprehensive one, is a composite measure. Other sub-sectors of the service industry e.g. high-touch hospitality versus high-tech financial services may be more interested in different dimensions of quality which are not fully reflected in our generalized model. Lastly, the paper fails to consider other external environmental factors, including differences in regulatory demands of AI data privacy and disparities in national digital infrastructure, which may affect the effectiveness of Digital Process Control. These limitations indicate that the model is sound, but it must be applied to particular organizational conditions and technological environments in the region.

Future Scope

The results of this research leave some opportunities to be developed in the future. With the further development of AI technology, namely with the emergence of generative models and autonomous agents, the meaning of Digital Process Control is likely to be extended. Further studies are required to explore the possibilities of generative AI to be utilized to not only supervise quality but also develop new quality processes dynamically. Moreover, even though this research was conducted in the context of the service industry, in general, the future work might use the model of multiple mediation on individual industries, such as healthcare, finances, logistics, etc., to determine whether industry-specific factors can change the mediation effects. The other potential field of research is the human-AI cooperation dimension; how the trust that employees in AI quality systems show to the digital control process determines the effectiveness of such digital controls may be the key to the better understanding of the soft side of digital TQM. Lastly, longitudinal studies of firms, which follow several years of AI adoption, would be invaluable in realizing long-term sustainability of these performance gains.

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