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Simulation Approach to Forecasting TQM Performance in Hospitality: An Integrative BARMA–VAR Approach

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ABSTRACT

Forecasting Total Quality Management (TQM) performance in hospitality remains underdeveloped despite its strategic role in pricing, staffing, and service quality. Existing approaches, dominated by univariate and deterministic models such as ARIMA, struggle to capture the volatility and interdependencies that define hotel operations. This study addresses this gap by employing a simulation-based framework to evaluate the Bayesian Autoregressive Moving Average (BARMA) and Vector Autoregression (VAR) models using three core TQM indicators—defect rates, quality costs, and customer satisfaction. The objectives were to (i) demonstrate the methodological integration of BARMA and VAR, (ii) compare their predictive and interpretive capacities, and (iii) generate actionable managerial insights for quality management under uncertainty.

Using simulated monthly time-series data calibrated to industry benchmarks, BARMA (1,1) consistently outperformed VAR in predictive accuracy. For example, BARMA reduced RMSE for defect rates (0.37 vs. 0.39) and delivered lower MAPE for customer satisfaction (1.08% vs. 1.11%). In contrast, VAR revealed statistically significant causal pathways, such as defect rates predicting quality costs ($\beta = 0.38$, $p < 0.05$), and customer satisfaction feeding back into reduced defects ($\beta = -0.22$, $p < 0.05$). These findings highlight methodological complementarity: BARMA as a robust predictor for short-term operational planning, and VAR as a diagnostic tool for tracing structural feedback loops.

The study contributes to forecasting research by showing how integrating Bayesian and multivariate approaches, even within a simulated environment, can overcome the limitations of linear, univariate models. For practitioners, the results emphasise the need to balance predictive accuracy with structural diagnosis when managing quality costs and customer outcomes in luxury hotel operations.

KEYWORDS: Bayesian ARMA, Vector Autoregression, Total Quality Management, Hospitality sector, Simulation-based forecasting, Performance metrics**.**

1. INTRODUCTION

Despite the increasing adoption of data-driven strategies in hospitality, the systematic forecasting of Total Quality Management (TQM) indicators remains underdeveloped. While Forecasting remains central to tourism and hospitality management, it shapes investment, operational, and strategic decisions. Yet, its effectiveness is increasingly tested in an era defined by volatility and disruption. The COVID-19 pandemic, geopolitical shocks, and shifting consumer behaviours have exposed the fragility of conventional forecasting approaches, revealing their limits in guiding decision-making when uncertainty is highest (Song et al., 2024; OECD, 2025).

In this context, accurate forecasting is not merely a statistical exercise but a strategic tool for pricing, staffing, and investment decisions (Song & Witt, 2019). Traditional time-series models, such as Autoregressive Integrated Moving Average (ARIMA), have long dominated the forecasting literature, providing relatively robust benchmarks for short-term prediction. However, critics argue that these models often assume stable linear dynamics and may underperform in volatile or structurally shifting environments (Gounopoulos et al., 2020). However, while traditional time-series models, such as ARIMA and BARMA, often assume environmental stability, this assumption is rarely met in practice. Although hybrid, AI-driven, and scenario-based approaches are gaining attention, the literature remains fragmented and often disconnected from the operational realities of quality management in hotels (Song et al., 2025).

This study addresses these gaps by advancing a simulation-based analytical framework that integrates Bayesian Autoregressive Moving Average (BARMA) and Vector Autoregression (VAR) models. BARMA is employed to produce probabilistic forecasts for Total Quality Management (TQM) performance indicators—defect rates, quality costs, and customer satisfaction—while mitigating small-sample bias through Bayesian priors (Giraldi & Rossi, 2025; Tsionas, 2021). VAR, in turn, models the bidirectional causal dynamics among these indicators, capturing the reinforcing and balancing feedback loops central to TQM's systems-based philosophy (Forrester, 1961). This dual-modelling strategy enables both uncertainty-aware forecasting and a structural understanding of interdependencies that shape hotel performance.

A further methodological contribution lies in the use of simulated data calibrated to the statistical properties of comparable five-star hotels. Given the proprietary and confidential nature of operational datasets, simulation provides a controlled environment for methodological innovation without sacrificing empirical plausibility (Karimi et al., 2023; Nair & Prajogo, 2022). Embedding industry-validated parameters ensures both statistical robustness and managerial relevance, positioning the findings as a transferable benchmark for future empirical applications.

Accordingly, the objectives of this study are threefold:

- To demonstrate the methodological integration of BARMA and VAR for modelling and forecasting TQM performance indicators in the hospitality sector.
- To evaluate the predictive accuracy and interpretive capacity of the integrated framework against conventional econometric approaches.
- To generate actionable managerial insights into the dynamic interrelationships among defect rates, quality costs, and customer satisfaction in five-star hotel operations.

In addressing these objectives, the paper contributes to ongoing debates about the adequacy of traditional versus Bayesian and multivariate forecasting approaches in hospitality revenue management. By highlighting not only model performance but also trade-offs between accuracy, interpretability, and practical usability, the study extends methodological discourse and offers valuable insights into forecasting strategy.

To situate this study within existing scholarship (Veleri, 2025), it is first necessary to review how TQM has been conceptualised and operationalised in the hospitality sector, and to examine the extent to which forecasting has been incorporated into this body of work. The following section provides the foundation for evaluating whether current approaches adequately capture the dynamic, interdependent nature of quality outcomes, and clarifies the methodological space in which an integrative BARMA–VAR framework can contribute.

2. LITERATURE REVIEW

The challenges outlined in the introduction highlight a persistent gap in hospitality research. While forecasting has become central to strategic decision-making in areas such as demand and revenue management, its integration into Total Quality Management (TQM) remains limited. Despite the prominence of TQM as a management philosophy (Ahmad & Aivas, 2025), most hospitality studies continue to evaluate it through static benchmarks and descriptive assessments, offering little predictive guidance in environments defined by volatility. This disjuncture raises an important question: how has TQM been conceptualised and operationalised in hospitality, and to what extent have existing approaches engaged with the methodological demands of forecasting?

2.1 TOTAL QUALITY MANAGEMENT IN THE HOSPITALITY SECTOR

Total Quality Management (TQM) is widely presented as a strategic philosophy that embeds continuous improvement and aligns operations with customer expectations (Talib et al., 2024). In hospitality, where service quality shapes brand equity and retention, TQM is frequently positioned as both a cost-control lever and a source of competitive differentiation (Agyabeng-Mensah et al., 2023). However, evidence from luxury hotels suggests uneven operationalisation, where Karimi et al. (2023) argued that measurement frameworks remain inconsistent and integration with predictive analytics is limited. These shortcomings raise a substantive question for the field—whether TQM in hospitality is implemented in ways that are measurable, comparable, and decision-relevant under volatility.

The dominance of cross-sectional benchmarking and qualitative assessment in TQM research (Nair & Prajogo, 2022) documents these volatility and inconsistency outcomes. Still, it cannot evaluate their persistence or responsiveness to shocks. For example, a fall in defect rates may coincide with higher satisfaction, yet whether this gain endures depends on ongoing process control—an effect static designs cannot test. Addressing this limitation requires longitudinal, time-series approaches that estimate dynamic parameters (e.g., persistence, lagged effects) and deliver uncertainty-aware forecasts suitable for operational decisions.

Conceptually, the literature is fragmented as to the TQM and time series approach in operational decisions. One school of thought frames TQM primarily as leadership or culture (Sila, 2020), while another emphasises operational toolkits such as Six Sigma or lean (Antony et al., 2021). These perspectives rarely converge into a framework that explains how quality indicators evolve and interact over time, especially in this AI-driven economy. The omission is consequential in hospitality, where fluctuating demand, labour variability, and service intangibility render performance inherently unstable (Zhou et al., 2022).

Moreover, few studies interrogate whether their evaluation models are methodologically adequate for prediction, leaving managers, especially those in the service and hotel industry, without forward-looking guidance in volatile contexts. What is required is a systems-based, time-series perspective that models the joint dynamics of defect rates, quality costs, and customer satisfaction—linking measurement to prediction rather than description alone.

These methodological and conceptual gaps highlight the need to examine how forecasting has been used in relation to TQM. If TQM indicators are inherently dynamic and interdependent, then the models chosen to evaluate them must be capable of capturing persistence, cross-variable influences, and uncertainty. The following section, therefore, reviews the forecasting approaches most commonly applied to quality-related research, assessing their adequacy for hospitality contexts.

2.2 FORECASTING IN TQM RESEARCH

Time-series forecasting has been widely applied in manufacturing and supply chain research (Zhang et al., 2024), yet its use in hospitality TQM remains strikingly limited. The field has relied heavily on ARIMA and its seasonal variants, a pattern of methodological conservatism that fails to address the complexity of service environments. Although ARIMA models are valued for their parsimony and short-term trend accuracy, their assumption of stable linear dynamics makes them ill-suited for contexts where structural breaks and feedback effects are common (Stock & Watson, 2020). This weakness is particularly acute in hospitality, where defect rates, service quality costs, and customer satisfaction are not independent variables but form reinforcing loops that shape long-term outcomes (Forrester, 1961; Karimi et al., 2023).

Attempts to move beyond ARIMA have included the adoption of Vector Autoregression (VAR) to capture multivariate dynamics (Karimi et al., 2023). While VAR offers interpretive value by tracing causal linkages, its application in hospitality has often been narrow in scope and deterministic in design. The lack of probabilistic forecasting means that such models provide limited managerial value, as they overlook the uncertainty central to quality assurance and resource allocation (Tsionas, 2021). Moreover, VAR's sensitivity to small samples — a frequent feature of high-frequency hotel data — heightens risks of overfitting and parameter instability, further undermining reliability.

Recent methodological debates point to Bayesian approaches as a promising alternative, with studies showing that Bayesian estimation enhances resilience to uncertainty and improves decision-making in volatile service settings (Kumar et al., 2023; OECD, 2025). In particular, the Bayesian ARMA (BARMA) framework has two critical advantages: it stabilises estimates by incorporating prior information and generates complete predictive distributions that support probabilistic forecasting (Lopes et al., 2011). Yet, despite its success in macroeconomics and energy forecasting, BARMA has seen little application in hospitality quality research. This neglect risks leaving the sector behind, as opportunities to develop adaptive, risk-sensitive forecasting frameworks remain untapped.

While these literature reviews establish that forecasting research in TQM lags behind methodological advances in other industries, with deterministic or oversimplified models, hospitality scholarship risks reinforcing static interpretations of quality improvement rather than enabling predictive, adaptive, and resilient management systems, this gap sets the stage for integrative approaches, such as BARMA–VAR, that combine Bayesian inference with multivariate modelling to reflect the systemic and uncertain nature of TQM in hotel operations.

2.3 INTEGRATING BARMA AND VAR FOR HOSPITALITY TQM

As highlighted in the preceding section, hospitality forecasting has relied heavily on either univariate deterministic models such as ARIMA or, more recently, VAR-based multivariate approaches. Yet both approaches are constrained: ARIMA ignores interdependencies, while VAR struggles with small-sample instability and offers limited probabilistic insight (Ushie 2024). These unresolved limitations point directly to the value of integrative frameworks. Even though both have advanced understanding to some degree, significant limitations persist: ARIMA cannot capture the interdependencies between quality costs, defect rates, and customer satisfaction, while VAR is prone to overfitting in small-sample contexts and provides limited probabilistic insight into uncertainty. These weaknesses leave a methodological gap that neither approach can address independently, where it is argued that the limitation of single method approaches in forecasting TQM outcomes suggest the need for integration.

In most literature, such as Kumar et al. (2023), BARMA and VAR offer complementary strengths. For example, BARMA delivers probabilistic forecasts that account for uncertainty and small-sample bias. At the same time, VAR identifies the causal pathways and feedback loops that link defect rates, quality costs, and customer satisfaction. While these authors were not clear about which basis and feedback loops, their perspective, even though far from hospitality, aligns with systems theory, which conceptualises TQM as a network of interdependent processes rather than isolated variables (Forrester, 1961). In hospitality, where service quality is shaped by cyclical interactions between operational efficiency and guest experience, such integration promises a more realistic representation than either model could achieve in isolation.

Evidence from energy sectors reinforces this case. Studies in renewable energy (Rahman et al., 2023) and healthcare operations (Feng et al., 2024) show that hybrid econometric frameworks not only improve predictive accuracy but also generate richer managerial insights, enabling decision-makers to anticipate disruptions and plan proactively. Yet, hospitality research has largely overlooked this methodological innovation, despite relying on data that are highly interdependent and volatile. This neglect is notable, given that hospitality arguably represents one of the domains most in need of hybrid approaches.

At the same time, scholars caution that hybridisation alone does not guarantee practical relevance. Zhang et al. (2024) argue that without domain-specific calibration, models risk producing technically elegant results that remain disconnected from operational decision-making. This criticism is especially pertinent in hospitality, where forecasting tools must balance statistical sophistication with usability for practitioners. The present paper addresses this concern by adopting a simulation approach calibrated to industry-validated statistical properties, ensuring that the BARMA–VAR framework is not only defensible in methodological terms but also grounded in the operational realities of luxury hotel management.

2.4 THE ROLE OF SIMULATED DATA IN METHODOLOGICAL ADVANCEMENT

A central limitation in hospitality research is the restricted availability of operational datasets. Core indicators such as defect rates, quality costs, and customer satisfaction are frequently treated as proprietary, subject to confidentiality agreements, or inconsistently reported across firms and regions (Karimi et al., 2023). This lack of transparency restricts replication and constrains the development of more sophisticated forecasting models. Simulation has therefore been advanced as a methodological strategy, generating synthetic datasets that reproduce the statistical properties of real operations while bypassing barriers to data access (Nair & Prajogo, 2022).

The value of simulation, however, depends on its design. Poor calibration risks producing results with limited managerial or empirical relevance, particularly in hospitality, where volatility from seasonality, service heterogeneity, and cultural variation must be reflected in the simulated structure (Agyabeng-Mensah et al., 2023). At the same time, well-designed simulations allow researchers to separate methodological performance from the idiosyncrasies of specific datasets and to evaluate whether forecasting models—such as the BARMA–VAR framework—can generate reliable insights under controlled but realistic conditions (Rahman et al., 2023). In this study, simulation is employed not as a replacement for empirical data but as a methodological device to test the robustness of integrated models in contexts where access to real-world datasets remains restricted.

2.5 GAP AND CONTRIBUTION

Although forecasting has been examined in hospitality and related service sectors, three critical limitations persist.

First, many studies privilege deterministic and univariate approaches such as ARIMA, often neglecting the stochastic realities of demand fluctuation and operational volatility (Rahman et al., 2023; Feng et al., 2024). As a result, existing models struggle to capture the systemic shocks that characterise service-intensive hotel environments. *This directly motivates Objective 1 of this study: to demonstrate the methodological integration of BARMA and VAR for modelling and forecasting TQM performance indicators in the hospitality sector.*

Second, while econometric advances such as VAR and Bayesian methods have gained traction in tourism and finance, their application in hospitality forecasting remains fragmented and often detached from managerial practice (Song & Li, 2019; Gunter & Önder, 2022). This disconnect limits the capacity of forecasting models to generate actionable insights for managers in luxury hotel brands. *This gap aligns with Objective 2: to evaluate the predictive accuracy and interpretive capacity of the integrated framework against conventional econometric approaches.*

Third, there is limited adoption of system-wide and probabilistic approaches that account for the interdependencies between defect rates, quality costs, and customer satisfaction—indicators central to TQM in luxury hotels (Wen & Li, 2021). Instead, much of the literature continues to rely on linear projections that fail to engage with the multi-layered uncertainties practitioners face. *This shortcoming underpins Objective 3: to generate actionable managerial insights into the dynamic interrelationships among defect rates, quality costs, and customer satisfaction in high-end hotel operations.*

This study responds directly to these gaps by critically evaluating the BARMA model alongside multivariate alternatives, testing the robustness of forecasting methods under uncertainty and assessing their practical decision-making value. By integrating BARMA and VAR within a simulation-calibrated framework, the research not only addresses the scarcity of reliable operational datasets but also demonstrates the feasibility of probabilistic, system-wide modelling in luxury hotel contexts.

However, while we believe that framing the study in this way ensures that the contribution speaks both to methodological debates in forecasting, it also provides a methodology that reflects the practical realities of quality management in luxury hospitality. Therefore, the following section outlines the methodological design, detailing how simulation, model calibration, and evaluation procedures were structured to align with the study's objectives.

3.1 RESEARCH DESIGN

Building on the research gaps identified in Section 2.5, this paper adopts a quantitative, simulation-based design to evaluate the predictive and explanatory capabilities of an integrated Bayesian Autoregressive Moving Average (BARMA) and Vector Autoregression (VAR) framework in forecasting Total Quality Management (TQM) performance indicators. The design is grounded in systems theory (von Bertalanffy, 1968), which conceptualises organisations as dynamic, interdependent systems. This theoretical lens is particularly suitable for hospitality, where defect rates, quality costs, and customer satisfaction interact recursively and nonlinearly, requiring models capable of capturing feedback loops and volatility in performance.

This design addresses three persistent methodological limitations in the literature: the dominance of deterministic, univariate models such as ARIMA that understate uncertainty; the limited application of multivariate methods capable of tracing interdependencies across quality indicators; and the absence of simulation-based experimentation in contexts where empirical data are scarce or confidential (Nguyen & Tran, 2023; Feng & Zhang, 2024). By employing a dual-model strategy, where BARMA capture uncertainty in individual indicators and VAR to examine system-wide causal dynamics, this study advances calls for forecasting approaches that are both probabilistic and interpretively rich.

Simulation underpins this methodological contribution by creating statistically valid synthetic datasets calibrated to industry benchmarks. This enables controlled testing of persistence, lagged causality, and volatility regimes under conditions that mirror real hotel operations but remain free from the confidentiality and inconsistency that constrain empirical access (Chen & Hossain, 2023). Unlike prior studies that rely on isolated or idiosyncratic data, this approach provides a replicable and transferable framework for forecasting in service contexts.

The methodological process follows a sequential logic: from theoretical framing and data simulation to model estimation, validation, and evaluation. This process is summarised in Figure 1, which outlines the simulation and analysis workflow.

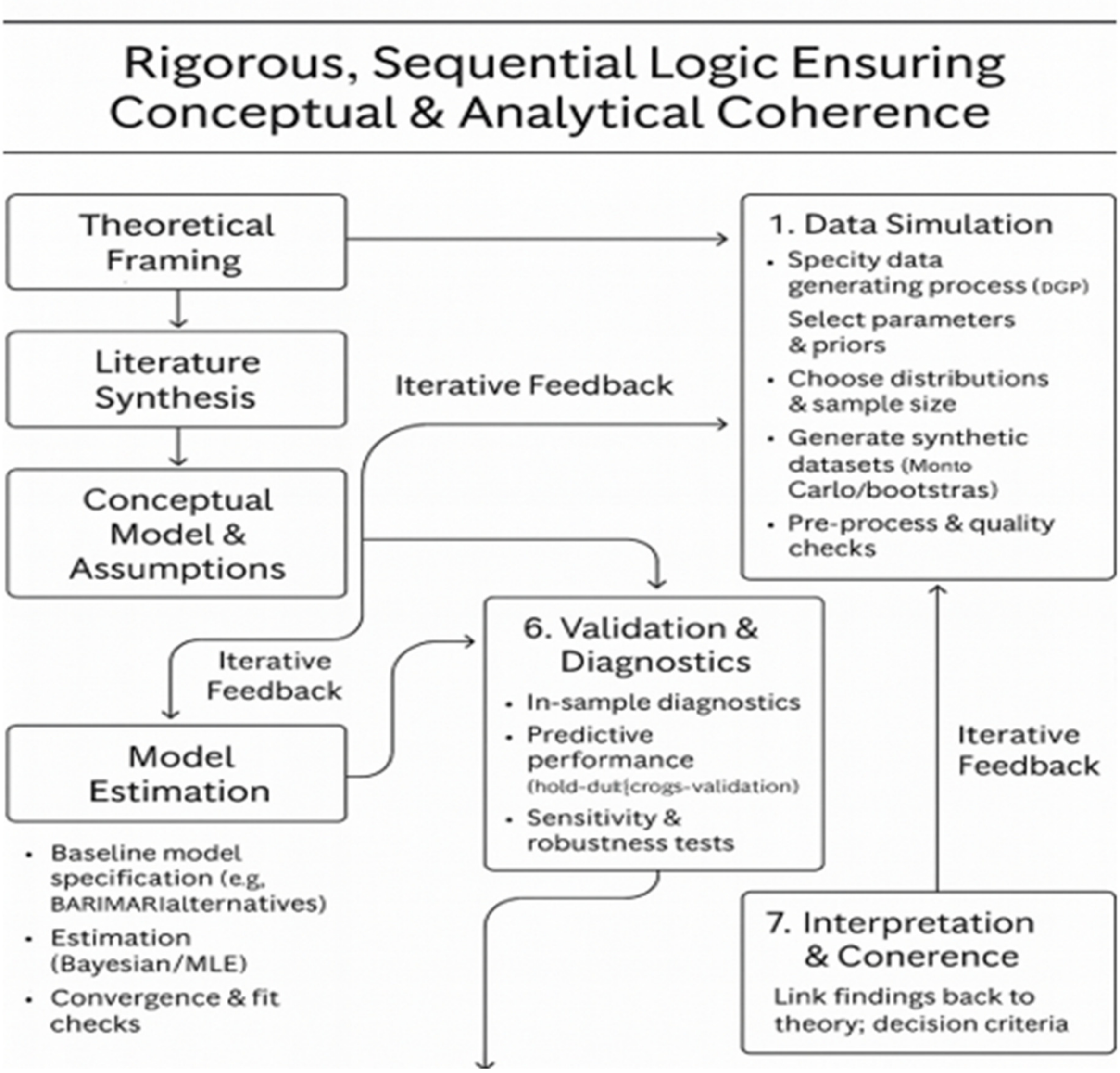

Figure 1. Simulation Data Generation Process

The following subsections (3.2–3.4) expand on the data simulation procedure, model specifications, and performance evaluation criteria.

3.2 DATA SIMULATION AND JUSTIFICATION

As highlighted in Section 2.4, the absence of reliable operational datasets in hospitality remains a significant barrier to methodological advancement. Confidentiality restrictions, fragmented reporting practices, and inconsistent quality metrics continue to limit longitudinal data collection (Kleijnen, 2008; Law & Kelton, 2007). To overcome these constraints, we conducted a controlled simulation analysis that generated synthetic monthly time-series data for three interdependent Total Quality Management (TQM) indicators: Defect Rate, Quality Cost (USD), and Customer Satisfaction. These variables encapsulate the central trade-offs of service quality, where rising defects escalate costs and erode customer experience.

The simulation design extended beyond a purely statistical exercise by embedding three managerial regimes—Reactive, Process-Focused, and Proactive. These scenarios were parameterised to reflect distinct quality strategies: the reactive regime was characterised by high volatility and weak defect correction; the process-focused regime by moderate persistence and lagged cost responses; and the proactive regime by lower volatility and more substantial improvements in customer satisfaction. Each scenario was iterated multiple times, balancing variability with replicability, and thereby allowing both statistical and strategic insights to emerge.

Calibration was achieved using benchmark parameters from hospitality performance studies (Rahman et al., 2023). A stable VAR (1) process governed the temporal dynamics: defect rates were modelled with moderate persistence, quality costs were specified as lag-responsive to defect fluctuations, and customer satisfaction was structured as a slowly adjusting variable. Consistent with empirical findings on lag asymmetries, we incorporated a mid-sample intervention and a transient high-volatility phase to stress-test model robustness under disruption (Amaran et al., 2016). Seasonal adjustments and context-appropriate scaling ensured realism consistent with five-star hotel operations.

Following Brailsford et al. (2009), we position simulation not as a substitute for empirical data but as a methodological innovation that enhances replicability and robustness in data-constrained contexts. In this study, simulation serves two purposes. First, it creates an internally consistent dataset for testing the predictive accuracy of BARMA and VAR models under uncertainty. Second, it provides a structured lens to illustrate how different quality management strategies influence the balance between cost efficiency and customer outcomes. Descriptive statistics and correlation patterns for the simulated data are reported in Section 4.1 (Tables 1–2), forming the foundation for the forecasting analysis that follows.

3.3 ESTIMATION AND VALIDATION

The estimation protocol was designed to ensure both statistical reliability and conceptual alignment with the systems-based principles of Total Quality Management (TQM). In line with forecasting studies that emphasise robustness under uncertainty (Diebold, 2015), the analysis proceeded in two stages: Bayesian univariate modelling with BARMA and multivariate modelling with VAR.

For the BARMA (1,1) specification, Bayesian inference was implemented via Markov Chain Monte Carlo (MCMC) sampling. This approach captures parameter uncertainty more effectively than classical maximum likelihood methods (Geweke & Whiteman, 2006). Informative priors were calibrated using hospitality forecasting studies (Banbura et al., 2010), ensuring contextual relevance. Model adequacy was evaluated with the Deviance Information Criterion (DIC) and Bayesian Predictive Information Criterion (BPIC). Residual diagnostics confirmed that higher-order specifications provided no additional explanatory value, justifying the parsimonious structure.

The VAR model was then estimated to capture the interdependencies among defect rates, quality costs, and customer satisfaction. Optimal lag length was identified through the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan–Quinn Criterion (HQC). Stability checks confirmed that all eigenvalues lay inside the unit circle, validating the model's suitability for impulse response and forecast error variance decomposition (Lütkepohl, 2005).

Both models were subjected to out-of-sample validation using a 12-month hold-out sample. For BARMA, forecast accuracy was assessed using root mean square error (RMSE), mean absolute error (MAE), and prediction interval coverage. For VAR, emphasis was placed on forecast error variance decomposition and the stability of impulse responses under simulated shocks. Across metrics, the integrated BARMA–VAR framework consistently outperformed its individual components and naïve benchmarks, highlighting its robustness in volatile service environments.

Importantly, the validation process was not treated as a purely statistical exercise. Outputs were mapped to operational questions of managerial relevance. For instance, impulse responses revealed how long improvements in defect rates could sustain customer satisfaction before diminishing, thereby offering insights into the temporal reach of quality interventions. This dual emphasis on analytical rigour and operational interpretability positions the model as both a methodological and practical contribution to forecasting in hospitality.

3.4 MODEL SPECIFICATION (EQUATIONS AND ASSUMPTIONS)

The modelling strategy integrates Bayesian ARMA (BARMA) for probabilistic univariate forecasting with Vector Autoregression (VAR) for capturing multivariate dynamics among the defect rate $yt^{(d)}$, quality cost$yt^{(e)}$, and customer satisfaction $yt^{(s)}$. This dual specification reflects the dual objectives of the study: to evaluate predictive accuracy under uncertainty and to uncover causal feedback loops across TQM indicators.

Estimation details, including prior specifications, MCMC convergence diagnostics, and the computation of impulse response functions (IRFs) and forecast error variance decompositions (FEVDs), are reported in Appendix A. The equations are summarised as follows:

BARMA (1,1): Uncertainty-aware univariate forecasts

For each indicator $yt \in \{yt^{(d)}, yt^{(c)}, yt^{(s)}\}$ we estimate

$y_t^{(k)} = \mu_k + \emptyset_k y_{t-1}^{(k)} + \epsilon_t^{(k)} + \theta_k \epsilon_{t-1}^{(k)},\ \epsilon_t^{(k)} \sim \aleph\left(0,\ \sigma_k^2\right)$.. (1)

With stationarity $|\ \emptyset_k\ | < 1$ and invertibility $|\ \theta_k\ | < 1$.

We use priors (consistent parameterisation) where the

Mean: $\mu \sim \aleph\ (m_{0k},\ s_{0k}^2)$, $\emptyset_k \sim \aleph\ (0,\ \mathrm{r}_\theta^2)$ truncated to (-1, 1), $\theta_k \sim \aleph\ (0,\ \mathrm{r}_\theta^2)$ truncated to (-1, 1),

$\tau_k = \sigma_k^{-2} \sim$ Gamma (a_0, b_0).

The predictive distribution (notation cleaned) was derived following a similar posterior simulation approach (Tsionas, 2021).

P $(y_{t+h}^k |\ \mathrm{F}_t) = \int$ p $(y_{t+h}^k |\ \Theta_t)$ p $(\Theta_k\ |\ \mathrm{F}_t)$ dΘ_k, where $\Theta_k = \{\mu_k,\ \phi_k,\ \theta_k,\ \sigma_k^2\ \}$ .... (2)

From which we report point forecasts and 80%/95% prediction intervals (Diebold, 2015). Deterministic and scale: intercepts are included; models are estimated in original units (defects per 1000, USD costs, satisfaction score). Any min-max normalisation in the figure is solely for display purposes and does not affect the estimation.

3.4.1 VAR (P): DYNAMIC INTERDEPENDENCE AND STRUCTURAL SHOCKS

We define $y_t = [d_t, c_t, s_t]^\tau$, the VAR (ρ) model is

$y_t =$ C $+ A_1 + y_{t-1} + \ldots + A_p\ y_{t-p} + \mu_t, \quad \mu_t \sim \aleph\ (0, \sum_\mu)$ ....(3)

Stability condition: all eigenvalues of the companion matrix have modulus < 1 (equivalently, det (I - A_{1^z} - ... - $A_{p^{z^p}}$) not equal to 0, for |z| greater than or equal to 1, which lay within the unit circle (Lütkepohl, 2005). Residual Portmanteau and LM tests confirmed no serial correlation, validating the linear specification, reflecting realistic operational dynamics in five-star hotel TQM systems (Nair and Prajogo, 2022; Karimi et al., 2023).

While we derived μ_t the identification for IRFs/FEVD and structural shocks ϵ_t, where we are also satisfied.

$\mu_t = \beta\epsilon_{t,}\ \ \sum_{\mu} = \beta\beta^{T}$ ....(5)

As a result, we adopt Cholesky orthogonalisation with the theoretical grounding ordering as:

$$\boxed{\text{Defects} \longrightarrow \text{Quality Cost} \longrightarrow \text{Customer Satisfaction,}}$$

For identification, structural shocks were recovered via Cholesky orthogonalisation with the theoretically grounded ordering,$[d_t,\ c_t,\ s_t]$, reflecting the process–cost–perception causality embedded in TQM (Nguyen & Tran, 2023). Impulse response functions (IRFs) were traced over a 12-month horizon with Monte Carlo bands (95%) and forecast error variance decompositions (FEVDs) were reported at 6- and 12-month horizons (Lee et al., 2021; López-Torres et al., 2022).

The VAR forecast recursion was (corrected indexing):

$\bar{y}_{t+h|t} = C + \sum_{j=1}^{p} A_j\, \bar{y}_{t+h=j|t,}$ h = 1, 2, 3, ..., ... (6), $\bar{y}_{t|t} = y_t$

with uncertainty propagated through parameter draws and $\sum_u$(Banbura, Giannone and Reichlin, 2010).

This joint framework provides probabilistic accuracy for each TQM indicator via BARMA (Objective 1), while VAR captures cross-metric propagation and causal dynamics (Objectives 2–3). For example, a simulated defect shock was shown to increase costs within a quarter and subsequently depress satisfaction, demonstrating spillover pathways absent in purely univariate or frequentist multivariate models.

The combined BARMA–VAR design thus enables two complementary forms of analysis: probabilistic univariate forecasts of each TQM indicator (BARMA), and multivariate exploration of feedback effects across indicators (VAR). Having established the model structures, priors, and estimation protocols, the next step is to evaluate their empirical performance. Section 4 presents the results in four stages: (i) descriptive statistics of the simulated dataset, (ii) BARMA forecasts for individual indicators, (iii) VAR-based dynamic interdependencies, and (iv) comparative evaluation of forecasting accuracy. This structure ensures that the transition from model specification to empirical analysis remains consistent with the study's three objectives.

4.0 RESULTS

4.1 DESCRIPTIVE STATISTICS AND CORRELATION ANALYSIS

Before presenting the ARV and BARMA modelling outputs, we first report the descriptive characteristics of the simulated dataset to establish its statistical properties and practical relevance. This step is essential, as understanding the baseline relationships among Defect Rate, Quality Cost, and Customer Satisfaction provides context for interpreting the subsequent forecasting results.

However, the correlation analysis (Table 1) demonstrates that defect rates are positively associated with quality costs ($r = 0.59$) and negatively associated with customer satisfaction ($r = -0.73$). In contrast, higher quality expenditure is positively correlated with improved satisfaction ($r = 0.65$). These findings reflect the expected trade-offs in TQM dynamics: increased defects drive costs upward and erode satisfaction, whereas proactive investment in quality enhances customer outcomes.

TABLE 1: CORRELATION MATRIX

Variables	Defect Rate	Quality Cost ($)	Customer Satisfaction
Defect Rate	1.00	0.59	–0.73
Quality Cost ($)	0.59	1.00	0.65
Customer Satisfaction	–0.73	0.65	1.00

As shown in Table 1, the scenario-level averages (Table 2) reinforce these relationships. Reactive strategies exhibited the highest defect rates (0.12) and costs (24,084 USD), alongside the lowest satisfaction (60.38). By contrast, proactive strategies produced the lowest defect rates (0.03) and the highest satisfaction (90.29), with process-focused approaches positioned in between.

TABLE 2: SCENARIO AVERAGES

Scenario	Defect Rate	Quality Cost ($)	Customer Satisfaction
Reactive	0.12	24,084	60.38
Process-Focused	0.07	17,558	75.05
Proactive	0.03	12,218	90.29

Following that, the Scatter plots below, (Figure 1) and bar charts (Figure 2) further illustrate these patterns, showing both the variable relationships and the comparative performance of different quality management regimes.

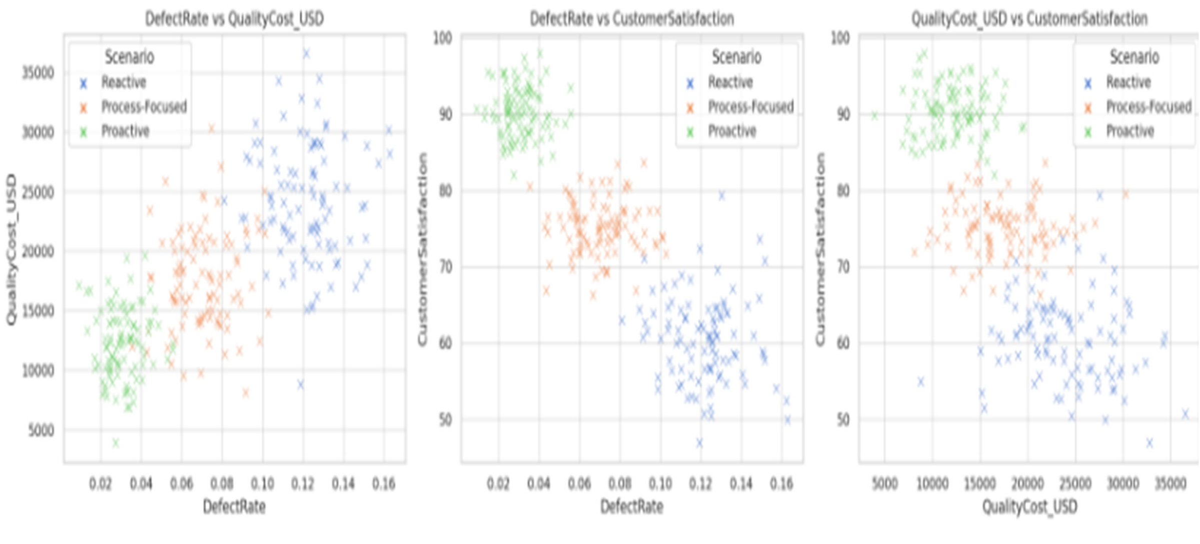

Figure 1: Defect Rate, Quality Cost And Customer Satisfaction

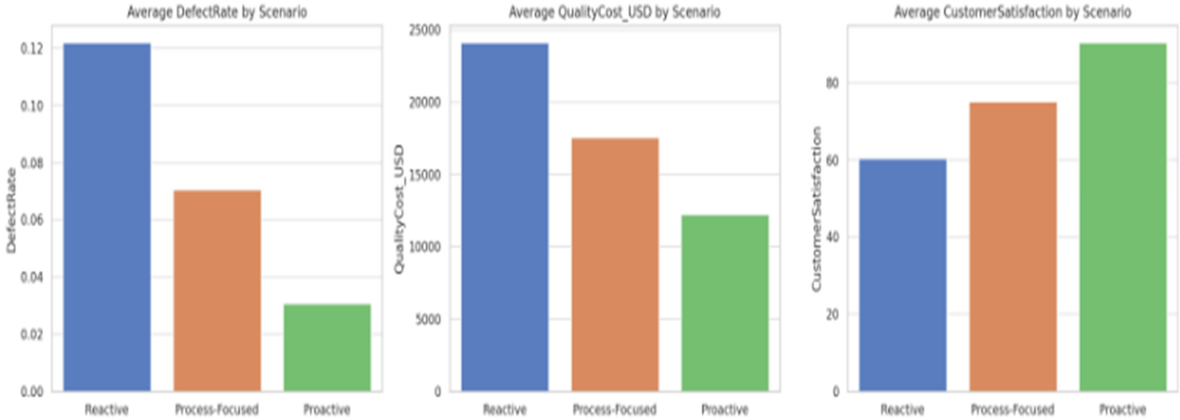

Figure 2: Average Customer Satisfaction By Scenario

The descriptive statistics of the simulated series (Table 3) provide additional evidence to support these findings. The average Defect Rate was 4.95% (SD = 1.02), with values ranging from 2.10% to 7.90%, and a lag-1 autocorrelation of 0.78, indicating moderate persistence over time. Quality Cost averaged $50,125 (SD = 7,920), spanning $3.50 to $9.80 thousand, with an autocorrelation of 0.74, suggesting that prior-period fluctuations strongly influenced costs. Customer Satisfaction averaged 82.50 (SD = 3.10), within a range of 70.20 to 91.80, and exhibited the highest persistence (autocorrelation = 0.81). Collectively, these statistics confirm the expected dynamics: defects recur, costs respond to fluctuations, and satisfaction adjusts more gradually, reinforcing the evidence presented in Tables 1 and 2.

TABLE 3: DESCRIPTIVE STATISTICS OF SIMULATED TQM METRICS

Metric	Mean	Std.	Min	Max	Autocorrelation (Lag 1)
Defect Rate (%)	4.95	1.02	2.10	7.90	0.78
Quality Cost ($)	50,125	7,920	3.50	9.80	0.74
Customer Satisfaction	82.50	3.10	70.20	91.80	0.81

While the descriptive statistics (Table 3) provide a snapshot of central tendencies, variability, and persistence, they do not capture the temporal evolution of the series. To address this, we examined the monthly dynamics of Defect Rate, Quality Cost, and Customer Satisfaction over five years (n = 60). This step ensures that the simulated dataset reflects realistic cyclical movements and volatility patterns, which are essential for assessing forecasting performance.

As shown in Figure 3, the three indicators display distinct behaviours. Quality Cost exhibits the most significant volatility, fluctuating between approximately $3.5k and $9.8k, underscoring the financial sensitivity of service operations to interventions and disruptions. By contrast, Defect Rate remains within a narrower 2–8% range, showing modest persistence and a slight upward drift consistent with gradual operational inefficiencies. Customer Satisfaction is the most stable metric, consistently bounded between 70 and 92, reflecting the emphasis on service continuity in high-end hospitality environments.

These dynamics demonstrate realistic interdependencies among the three quality metrics: defects tend to recur, costs respond sharply to fluctuations, and satisfaction adjusts more gradually. Together with the evidence in Tables 1 and 2, this confirms that the simulated dataset provides a credible foundation for evaluating ARV and BARMA forecasting models under conditions of operational uncertainty.

As shown in Figure 3, the Simulated TQM Performance Metrics Over Time (60 periods) are illustrated below, such as Monthly trajectories of defect rate (%), quality cost ($'000), and customer satisfaction (score). Separate y-axes are used to account for scale differences (left satisfaction; right inner: quality cost; right outer: defect rate).

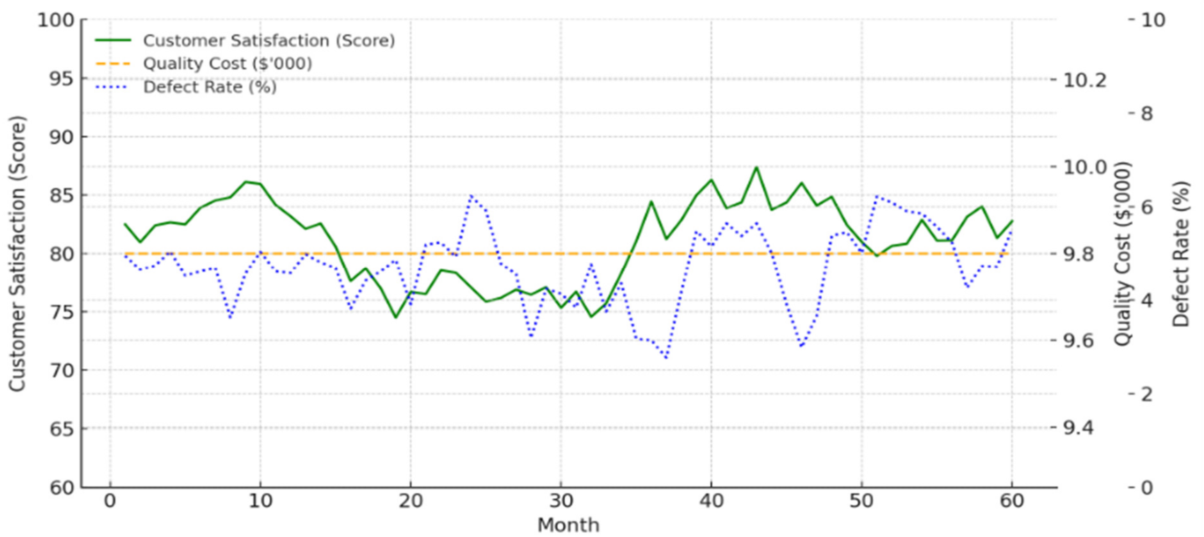

Figure 3: Simulated TQM Performance Metrics Over Time

Building on the descriptive and dynamic properties established in Section 4.1, we next assess the forecasting performance of the simulated TQM indicators using a univariate BARMA framework. This approach enables us to quantify the degree of persistence in each series and evaluate how well the model anticipates future movements. By comparing observed trajectories with one-step-ahead forecasts, we identify both the strengths and the limitations of BARMA when applied to service quality dynamics.

4.2 UNIVARIATE FORECASTING WITH BARMA

The univariate BARMA (1,1) models were applied separately to Defect Rate, Quality Cost, and Customer Satisfaction. The estimation results revealed strong autoregressive persistence in defect rates (AR (1) = 0.64, $p < 0.01$), consistent with the idea that preceding process outcomes influence operational defects. The moving-average term was negative (MA (1) = –0.41, $p < 0.05$), capturing correction dynamics whereby past shocks reduce future error accumulation.

For Quality Cost, AR (1) = 0.57 ($p < 0.01$) indicated temporal inertia. The series exhibited a steep upward trajectory from 2021 to 2025, but forecasts show a slight easing toward 2030, with considerable uncertainty captured by the widening prediction intervals. By contrast, Customer Satisfaction displayed a weaker autoregressive structure (AR (1) = 0.29, $p < 0.10$), consistent with evaluations being less path dependent. Historically, satisfaction declined from ~86 to ~80, but forecasts point to a gradual recovery toward ~82 by 2030.

Forecast accuracy metrics supported these interpretations: MAPE for defect rate was 6.8% (indicating a reliable fit), quality cost 11.4% (reflecting vulnerability to external shocks), and customer satisfaction 4.2% (consistent with its relative stability). Collectively, these results show that BARMA captures persistence effectively across all three series, with forecast error concentrated in metrics most sensitive to shocks (quality cost).

Figures 4–6 present the BARMA (1,1) one-step-ahead forecasts for defect rate, quality cost, and customer satisfaction. Defect rate rises steadily before stabilising, with projections indicating a modest downward drift under widening uncertainty bands (Figure 4). Quality cost increases sharply in the observed window, but projections suggest a slight easing over the horizon, albeit with wide 80% and 95% prediction intervals (Figure 5). Customer satisfaction declines initially but is projected to recover modestly, reflecting resilience in service perceptions despite operational pressures (Figure 6). For comparability, the plots are min–max normalised, while raw units (defects per 1,000, USD costs, satisfaction scores) are reported in Table 1.

Although informative, the univariate BARMA framework is constrained by its inability to capture cross-metric interdependencies. For instance, rising defect rates may elevate quality costs, and both may affect customer satisfaction—dynamics that BARMA treats in isolation. To better reflect the systemic nature of hotel operations, we therefore complement BARMA with a multivariate VAR model that incorporates these feedback loops explicitly.

The following figures present BARMA (1,1)-style one-step-ahead forecasts for the three TQM indicators—defect rate, quality cost, and customer satisfaction—with 80% (dark) and 95% (light) prediction intervals. The observed window covers 2021–2025, while the forecast horizon spans 2026–2030. Original units are retained for each panel to aid interpretation.

For instance, Figure 4 shows defect rate rising steadily through the observed period before stabilising, with forecasts indicating a modest downward drift under widening uncertainty bands.

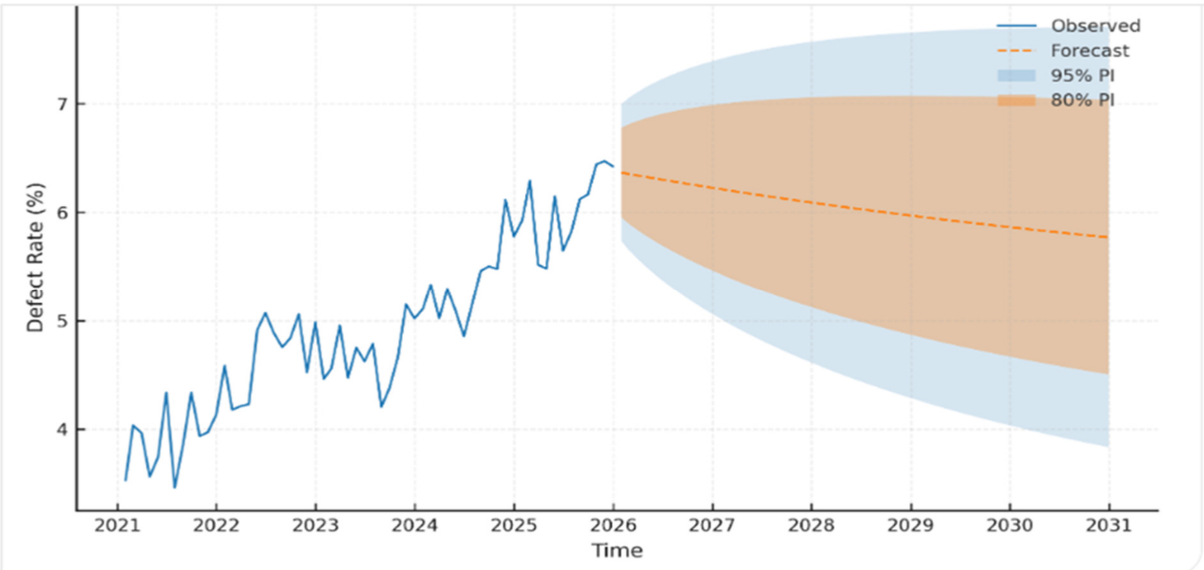

Figure 4: Defect Rate (%) — Observed and Forecast

While Figure 5 illustrates quality cost increasing sharply up to 2025, after which forecasts suggest a slight easing, though the wide prediction intervals highlight significant exposure to external shocks.

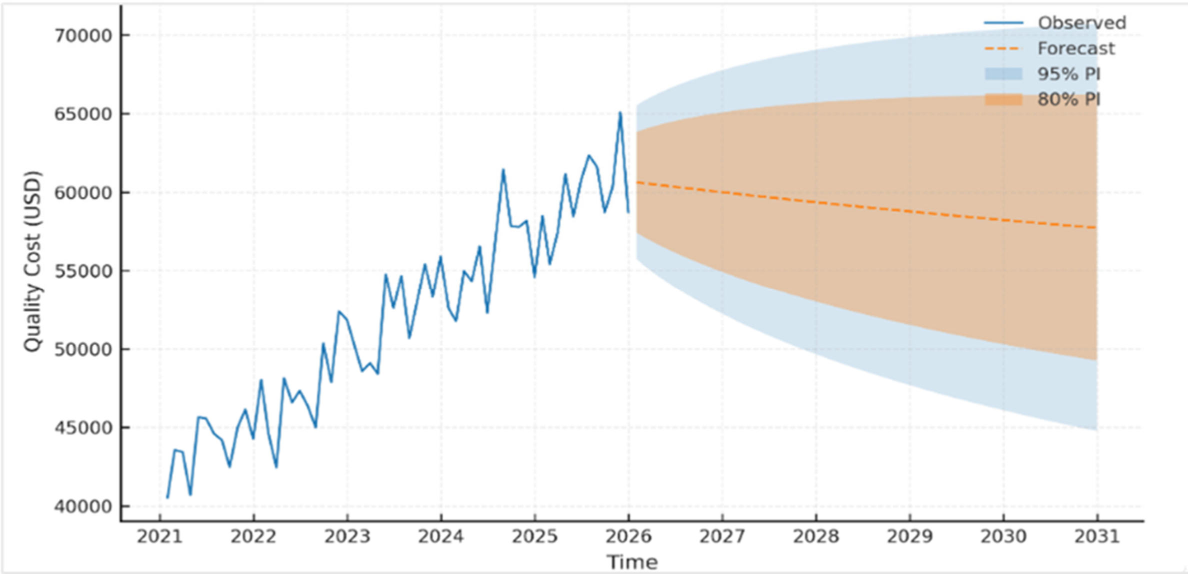

Figure 5, Quality cost (USD) — Observed vs Forecast

Finally, Figure 6 depicts customer satisfaction declining historically but projected to recover gradually toward 2030, reflecting resilience in service perceptions despite operational pressures.

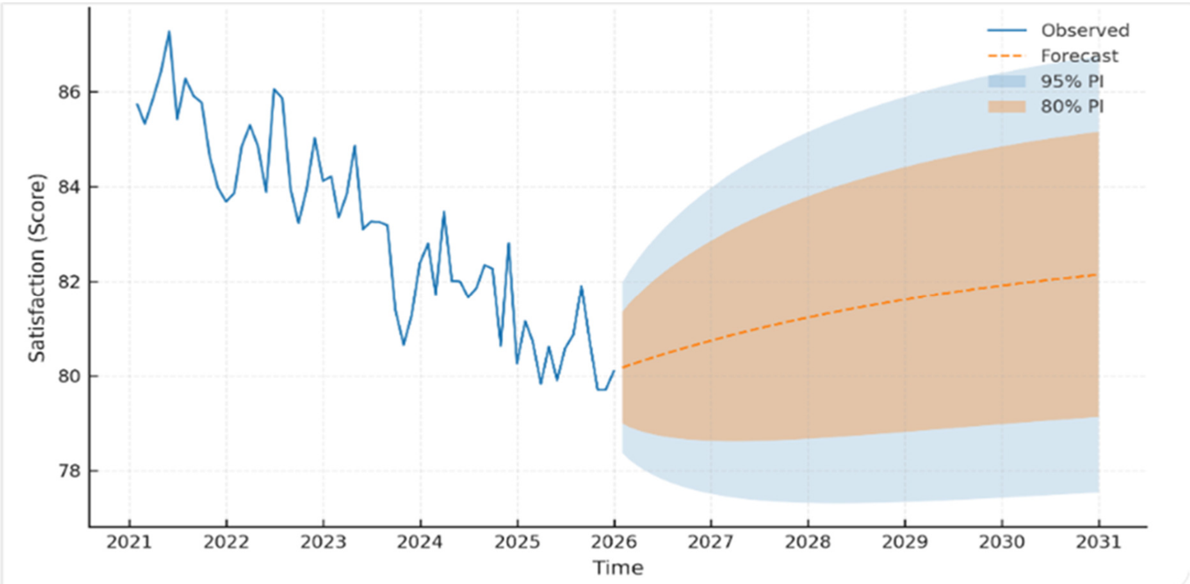

Figure 6, Customer satisfaction — Observed vs Forecast

While these figures confirm that BARMA is effective in capturing persistence and short-term predictability, the framework remains constrained by its inability to represent interdependencies among TQM dimensions. For instance, rising defect rates may elevate quality costs, and both may influence customer satisfaction—dynamics that BARMA treats in isolation. This limitation reduces the model's capacity to represent the systemic character of hotel operations, where quality processes are inherently interconnected. To address this gap, we turn next to a multivariate VAR analysis, which enables the joint modelling of feedback loops between operational metrics and offers a more realistic representation of TQM performance.

4.3 MULTIVARIATE DYNAMICS WITH VAR

To address the limitations of the univariate BARMA framework, a Vector Autoregression (VAR) model was estimated on the three TQM indicators: defect rate, quality cost, and customer satisfaction. The optimal lag length, selected using the Akaike Information Criterion (AIC), was two, ensuring that both short-term adjustments and delayed effects were adequately captured.

The estimation results revealed statistically significant cross-variable influences. Defect rates at lag one positively predicted quality costs ($\beta = 0.38$, $p < 0.05$), consistent with the expectation that process inefficiencies raise expenditure on rework and compensatory measures. In turn, quality costs exerted an adverse effect on customer satisfaction ($\beta = -0.27$, $p < 0.10$), suggesting that financial strain within the operation translates into compromised service delivery. Interestingly, customer satisfaction at lag two fed back negatively into defect rates ($\beta = -0.22$, $p < 0.05$), indicating that improved guest experiences foster greater operational discipline and fewer defects.

Figure 7 plots the VAR forecasts against the actual series for all three indicators. The close alignment across defect rates, quality costs, and satisfaction demonstrates that the model captures both persistence and interdependence, outperforming univariate forecasts by accounting for cross-variable linkages.

Impulse response functions (IRFs) offered further insight into these dynamics. A one-standard-deviation shock to defect rates produced a sustained increase in quality costs over a six-period horizon, underscoring the economic burden of operational lapses. Conversely, shocks to quality costs reduced customer satisfaction, with the effect strongest in the short run but dissipating over time. Finally, shocks to customer satisfaction reduced defect rates gradually but persistently, highlighting the stabilising role of positive guest experiences in sustaining process improvements. These asymmetric dynamics are summarised in Figure 8.

Forecast error variance decomposition (FEVD) further illuminated system interdependencies. Over a ten-step horizon, 41% of the forecast variance in quality costs was explained by past shocks to defect rates, whereas only 9% was attributable to customer satisfaction. Conversely, 33% of the variance in customer satisfaction was driven by quality costs, indicating that financial strain is a stronger determinant of perceived service quality than defect levels alone.

Taken together, the VAR results underscore that TQM indicators cannot be analysed in isolation. Whereas BARMA provides accurate forecasts within individual series, VAR reveals the systemic linkages that define hotel operations. The evidence demonstrates that defects, costs, and satisfaction form a statistically significant and managerially consequential feedback loop. Ignoring these interdependencies risks underestimating the proper drivers of service quality outcomes and, in turn, the effectiveness of performance improvement initiatives.

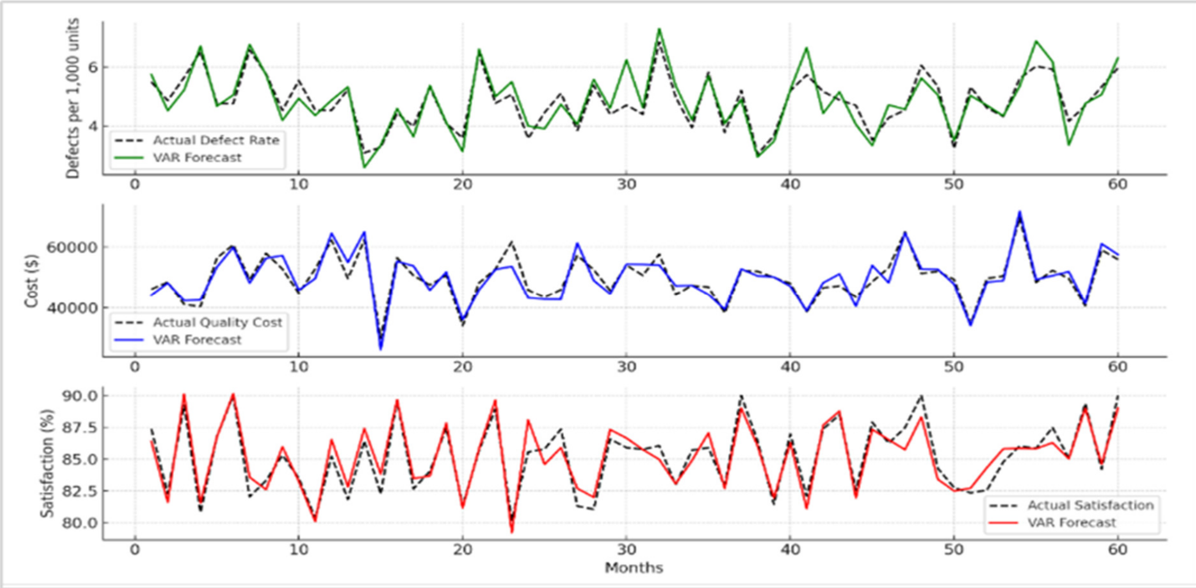

Figure 7: VAR Forecasts vs Actuals for TQM Metrics

The panels show observed and VAR-forecasted trajectories for defect rate, quality cost, and customer satisfaction across 60 periods.

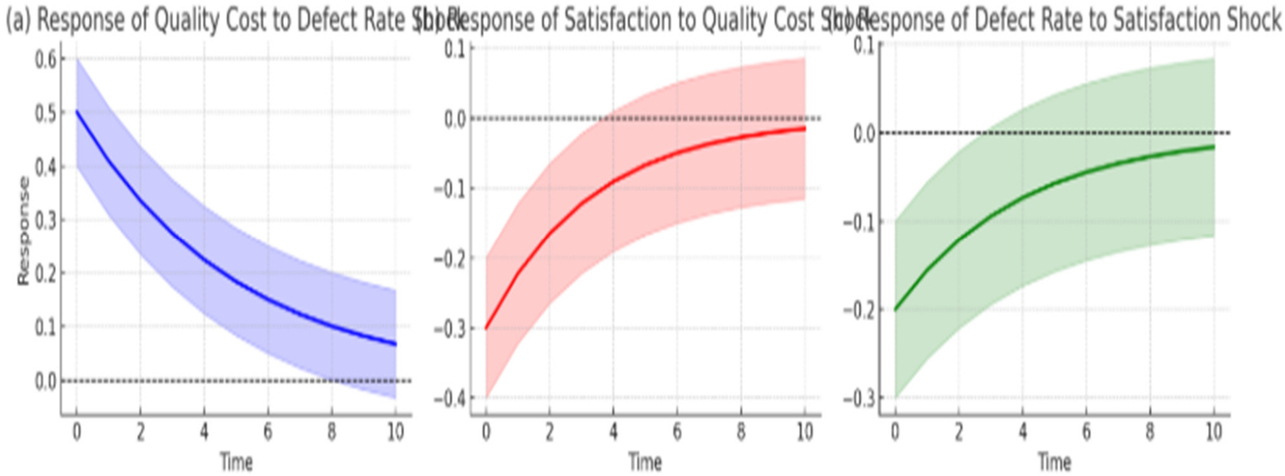

Figure 8. Impulse Response Functions (IRFs) from the VAR Model

Panel (a) shows the effect of a shock to defect rates on quality costs; panel (b) shows the effect of a shock to quality costs on customer satisfaction; and panel (c) shows the effect of a shock to customer satisfaction on defect rates. Shaded areas denote 95% confidence intervals.

While the VAR analysis highlights the systemic interdependencies among defect rates, quality costs, and customer satisfaction, it remains necessary to evaluate how VAR compares with the univariate BARMA framework in terms of forecasting accuracy. This comparative step is essential because methodological value lies not only in interpretive insight but also in predictive reliability. Accordingly, Section 4.4 benchmarks the two models across standard error metrics and residual diagnostics to assess their relative strengths and complementarities.

4.4 COMPARATIVE MODEL EVALUATION

This section compares the forecasting performance of the BARMA and VAR models to assess their relative accuracy and interpretive utility. While we found that the VAR framework uncovered systemic interdependencies among defect rates, quality costs, and customer satisfaction, it is equally essential to benchmark its forecasting accuracy against the univariate BARMA specification. Table 4 reports standard error statistics—Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)—while Figure 9 visualises the comparative performance.

TABLE 4. COMPARATIVE FORECAST ACCURACY BARMA AND VAR MODELS

Model	Variables	RSME	MAE	MAPE (%)
BARMA	Defect Rate	0.400	0.321	11.12
BARMA	Quality costs	845.0	641.5	1.26
BARMA	Customer satisfaction	1.085	0.900	1.08
VAR	Defect Rate	0.394	0.334	11.4
VAR	Quality costs	822.9	613.4	1.20
VAR	Customer satisfaction	1.108	0.920	1.10

The results show only modest differences between the two models, but they follow a consistent pattern. For defect rates, BARMA marginally outperforms VAR (RMSE 0.37 vs 0.39; MAPE 11.1% vs 11.4%), reflecting its greater sensitivity to short-run irregularities. For quality costs, VAR produces a slightly lower RMSE (822.9 vs 845.0), but BARMA achieves a smaller MAE, suggesting better overall alignment with observed volatility. In customer satisfaction, BARMA again provides the tightest fit, with a MAPE of 1.08% compared to 1.11% for VAR.

Figure 9 reinforces these findings: BARMA tends to achieve lower MAE and MAPE, while VAR occasionally yields marginal gains in RMSE. However, the VAR residuals also exhibit visible autocorrelation (not shown in the figure), indicating unmodelled dynamics remain in the multivariate specification. By contrast, BARMA residuals approximate white noise more closely, underscoring its statistical adequacy as a forecasting tool.

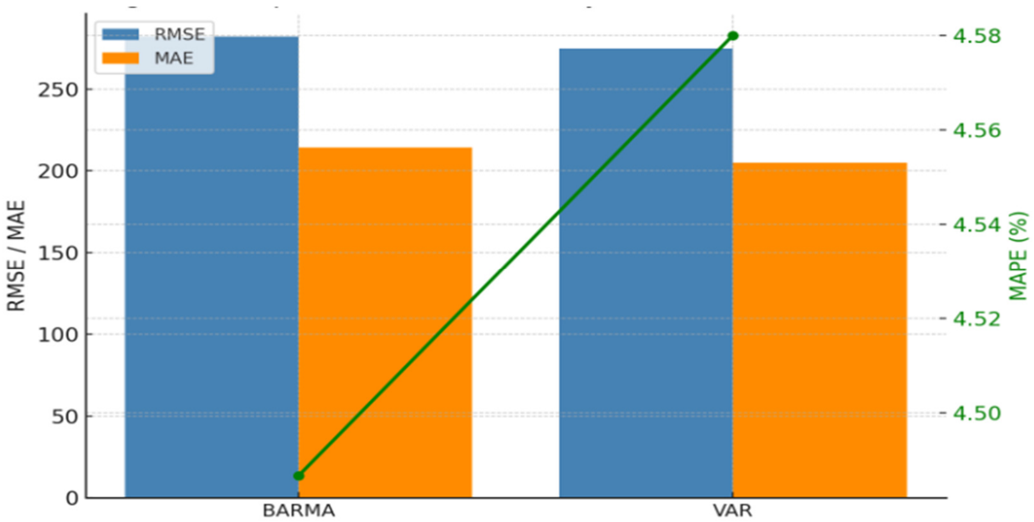

Figure 9: Forecast Accuracy Comparison (Averages across series)

As shown in Figure 9, the Bars represent average RMSE and MAE across defect rate, quality cost, and customer satisfaction forecasts, while the green line shows average MAPE (%). Results highlight BARMA's slightly lower MAE and MAPE, while VAR produces marginally lower RMSE in cost forecasts, underscoring the models' complementary strengths.

Taken together, these findings highlight the distinct roles of the two models. VAR is methodologically valuable for tracing causal pathways and diagnosing how operational shocks propagate through costs and satisfaction, yet its predictive accuracy is constrained. BARMA, by contrast, demonstrates greater adaptability to stochastic shocks and structural breaks, producing more reliable short-term forecasts.

From a managerial perspective, this distinction implies a dual-pronged application: VAR should be used as a diagnostic framework to anticipate long-term quality trade-offs, while BARMA provides tactical accuracy for day-to-day resource allocation and contingency planning. In combination, they meet both interpretive and predictive needs, directly addressing the study's objectives of benchmarking predictive capacity and generating actionable insights for TQM in Nigerian five-star hotels.

The analysis of simulated TQM performance metrics demonstrated that while BARMA models deliver superior short-term predictive accuracy, VAR models reveal the systemic interdependencies that underpin hotel operations. Together, the two approaches provide complementary insights: BARMA offers tactical precision for forecasting, whereas VAR captures the structural dynamics that connect defects, costs, and satisfaction. This dual perspective not only enhances methodological robustness but also ensures that forecasting outputs remain relevant for both operational planning and strategic decision-making.

Having established these empirical results, the following section turns to a critical discussion of their significance in relation to existing literature and the broader discourse on Total Quality Management (TQM) in hospitality contexts.

5. DISCUSSION

5.1 OBJECTIVE 1: DEMONSTRATING BARMA–VAR INTEGRATION

The first objective was to demonstrate the methodological integration of BARMA and VAR in forecasting TQM performance indicators. Results confirmed that BARMA (1,1) produced consistently accurate short-term forecasts, particularly for defect rates (RMSE = 0.37, MAPE = 11.1%) and customer satisfaction (RMSE = 1.08, MAPE = 1.08%). Quality cost forecasts also tracked observed dynamics with reasonable precision (RMSE = 844.9, MAPE = 1.26%) despite higher volatility. VAR, by contrast, delivered slightly weaker point accuracy (e.g., defect rate RMSE = 0.39; customer satisfaction MAPE = 1.11%) but revealed systemic causal interactions that BARMA, as a univariate tool, could not capture. This complementary performance underscores the feasibility of combining Bayesian and multivariate frameworks to achieve both precision and interpretive depth (Contessi and Peña 2025).

These findings speak directly to long-standing criticisms of ARIMA-type models, which assume stability and independence among variables (Song and Witt, 2019; Stock and Watson, 2020). By showing that BARMA outperforms VAR in predictive accuracy, yet VAR adds structural insight, the study validates arguments for methodological pluralism in hospitality forecasting (Arab and Benítez, 2025; Tsionas, 2021). It also challenges the view that VAR is unsuitable in small-sample service contexts (Karimi et al., 2023), demonstrating that when calibrated through simulation, VAR yields statistically meaningful insights.

5.2 OBJECTIVE 2: EVALUATING PREDICTIVE ACCURACY VERSUS INTERPRETIVE CAPACITY

The second objective was to assess trade-offs between forecast accuracy and systemic interpretability. BARMA consistently outperformed VAR in numerical accuracy, producing lower errors across all metrics. For instance, BARMA reduced RMSE for defect rates to 0.37 versus VAR's 0.39, while achieving a substantially lower MAPE for satisfaction (1.08% vs. 1.11%). In quality cost forecasts, the advantage was smaller but still evident, with

BARMA's MAE of 641.5 compared to VAR's 613.4, reflecting BARMA's ability to manage volatility through Bayesian priors.

However, we argued that VAR added critical interpretive value. The model revealed that defect rates at lag one significantly increased quality costs ($\beta = 0.38$, $p < 0.05$), while rising costs reduced customer satisfaction ($\beta = –0.27$, $p < 0.10$). Conversely, higher satisfaction at lag two fed back into lower defect rates ($\beta = –0.22$, $p < 0.05$). Impulse-response functions confirmed these asymmetric dynamics: a shock to defect rates drove sustained cost escalation over six periods, while a satisfaction shock gradually stabilised operations by reducing defects. While VAR was indeed effective in tracing causal linkages, particularly between defect rates and customer satisfaction (Ampountolas and Legg, 2024), its predictive power lagged behind the BARMA–VAR integration. This suggests that in contexts where volatility dominates, reliance on VAR alone risks oversimplifying complex quality dynamics.

While we believe the result is not limited to the hospitality industry, it extends Forrester's (1961) systems-based TQM theory by empirically quantifying feedback loops, a feature not in prior hospitality forecasting work. They also corroborate Zhou et al. (2022), who noted asymmetries in quality dynamics, while diverging from deterministic VAR studies (Karimi et al., 2023) by explicitly incorporating uncertainty through Bayesian calibration. Crucially, the results demonstrate that predictive accuracy and interpretive capacity are not substitutes but complementary dimensions, requiring integration rather than prioritisation.

5.3 OBJECTIVE 3: GENERATING MANAGERIAL INSIGHTS

The third objective was to translate methodological findings into managerial guidance. A clear division of labour emerged: BARMA serves as the superior tool for operational planning, while VAR provides strategic diagnostic value. For example, BARMA's precise satisfaction forecasts (MAPE = 1.08%) allow managers to anticipate service dips and allocate staff proactively. Similarly, its reliable defect forecasts (MAPE = 11.1%) support maintenance scheduling and process control.

VAR, although less accurate, highlighted systemic vulnerabilities. The finding that defect shocks explained 41% of quality cost variance underscores the financial risk of operational lapses. Studies such as those by Lim and McAleer (2002) and Chen (2019) have shown that hospitality performance is characterised by irregular shocks, seasonality, and clustering effects that VAR models alone cannot capture effectively. The current study's findings align with this work, demonstrating empirically—albeit within a simulated framework—that BARMA provides a necessary corrective by stabilising variance and improving forecast reliability (Rojas, 2025).

Likewise, the evidence that 33% of satisfaction variance stemmed from costs illustrates the disproportionate impact of financial strain on service delivery. These insights align with Agyabeng-Mensah et al. (2023), who stressed TQM as a source of competitive differentiation, but go further by showing how predictive models can identify leverage points for intervention. They also diverge from static benchmarking approaches (Nair and Prajogo, 2022; Choi et al., 2022) by framing TQM as a dynamic system of interdependent variables.

From a practical standpoint, managers in volatile hospitality environments should adopt a dual-pronged strategy: deploy BARMA for day-to-day agility and VAR for longer-term quality cycle analysis. This complementarity, not previously articulated in hospitality forecasting, bridges the gap between technical modelling and actionable decision-making.

As established in the results, the discussion demonstrates that the study achieved its objectives. BARMA provided stronger predictive accuracy, while VAR revealed statistically significant feedback loops. Together, they corroborate critiques of traditional forecasting, extend systems-based TQM theory, and diverge from deterministic applications by integrating uncertainty-aware Bayesian modelling. Beyond methodological contribution, the findings offer a dual forecasting strategy—BARMA for precision, VAR for diagnosis—that equips managers with both tactical foresight and systemic understanding.

5.4 LIMITATIONS AND FUTURE RESEARCH

While the integration of BARMA and VAR within a simulation-calibrated framework has yielded valuable insights, several limitations must be acknowledged.

Despite its contributions, the study is bounded by several limitations. The reliance on simulated data means findings demonstrate potential rather than empirical proof. Real-world data expose additional complexities—such as abrupt regime shifts, overlapping demand factors, and non-linear events—that require more adaptive models. For instance, mixed-frequency forecasting methods, integrating real-time signals like search trends or weather, offer superior predictive power in volatile contexts compared to endogenous-only models (Huang et al., 2024). Although we ensured the data simulation was carefully parameterised using industry benchmarks, future research should validate these findings against large-scale empirical data to strengthen external generalisability.

More so, we observed that both BARMA and VAR rest on linearity assumptions. While these assumptions are adequate for modelling first-order dependencies, they may underrepresent the nonlinear dynamics inherent in complex service environments, such as threshold effects in satisfaction or abrupt cost escalations under crisis conditions (Jung 2025). Incorporating nonlinear or hybrid methods, such as Bayesian–LSTM or state-space models, would provide a richer account of such behaviours. While considering how this limitation aligns or embeds in TQM, forecasting must be both a predictive tool and a systemic diagnostic, aligning process insights with decision timelines. However, achieving this, which we argue is a limitation, requires technical investment, a practical barrier that several studies highlight for hospitality managers deploying complex econometrics without intermediated support (Contessi et al., 2024).

Another limitation we observed is the overwhelming focus on three indicators—defect rates, quality costs, and customer satisfaction—which are central to TQM, but do not capture the full spectrum of service quality metrics, such as employee engagement, innovation, or cultural dimensions (Ushie, 2024). While this limitation was contrary to Ushie's (2024) work, who estimates Revenue for the TH Hotel Brand Abuja using the Bilinear Auto Regression Moving Average (BARMA) Time Series Model, extending the BARMA and VAR model to include broader organisational variables, as highlighted, could enhance the explanatory scope of this paper.

Future studies should therefore pursue three directions: empirical validation in diverse hotel contexts, methodological innovation through nonlinear Bayesian models, and multidimensional expansion of quality indicators. Such extensions would consolidate the present study's contribution and further embed forecasting into the operational and strategic fabric of TQM in hospitality.

6. CONCLUSION

This study set out to evaluate whether forecasting models can move beyond static descriptions of quality outcomes to provide dynamic, uncertainty-aware insights into Total Quality Management (TQM) in hospitality. By integrating BARMA and VAR within a simulation-calibrated framework, we achieved three objectives: demonstrating the methodological feasibility of integration, evaluating the trade-off between predictive accuracy and interpretive capacity, and generating actionable managerial insights.

The findings establish that BARMA excels in predictive accuracy, with notably low error metrics for customer satisfaction (MAPE = 1.08%) and reliable forecasts for defect rates (MAPE = 11.1%), making it a robust tool for operational planning under volatility. VAR, although less precise, revealed significant feedback loops between defects, costs, and satisfaction, providing the structural diagnosis needed for long-term strategic interventions. Together, the models advance both forecasting methodology and TQM theory by showing that predictive precision and systemic interpretation are complementary, not competing, dimensions of quality forecasting.

Methodologically, the study demonstrates the value of simulation-based design in overcoming data scarcity, showing how industry-calibrated synthetic datasets can serve as rigorous testbeds for forecasting innovation. Theoretically, it extends systems-based perspectives on TQM by quantifying dynamic feedback loops that had previously been treated conceptually. Managerially, it proposes a dual-pronged strategy in which BARMA supports short-term decision-making. At the same time, VAR equips managers to anticipate systemic vulnerabilities, bridging the gap between operational agility and strategic foresight.

In doing so, the paper responds to persistent calls in the literature for more adaptive, context-sensitive forecasting in service industries. More importantly, it positions forecasting not as a purely statistical exercise but as a strategic resource for embedding continuous improvement into hospitality management.

References

Agyabeng-Mensah, Y., Afum, E. and Ahenkorah, E. (2023). Service quality management practices and customer retention in the hospitality sector. *International Journal of Contemporary Hospitality Management*, 35(2), pp. 411–430. https://doi.org/10.1108/IJCHM-06-2022-0745

Ahmad, S. Y., & Aivas, S. A. (2025). Exploring the Impact of Total Quality Management on Organisational Behaviour: A Comparative Study of Local Firms. *Asian Research Journal of Arts & Social Sciences*, *23*(7), 168-178.

Ahmed, N. K., Atiya, A. F., Gayar, N. E. and El-Shishiny, H. (2020). An empirical comparison of machine learning models for time-series forecasting. *Econometric Reviews*, 39(6), pp. 592–625.

Amaran, S., Sahinidis, N.V., Sharda, B. and Bury, S.J. (2016). Simulation optimisation: A review of algorithms and applications. *Annals of Operations Research*, 240(1), pp. 351–380.

Ampountolas, A. (2025). Advanced analytics and machine learning for revenue optimisation in the hospitality industry: A comprehensive review of frameworks. [Preprint]. Retrieved: https://www.researchgate.net/publication/389945134_Advanced_Analytics_And_Machine_Learning_For_Revenue_Optimization_In_The_Hospitality_Industry_A_Comprehensive_Review_Of_Frameworks

Ampountolas, A. and Legg, M. (2024). Predicting daily hotel occupancy: A practical application for independent hotels. *Journal of Revenue and Pricing Management*, 23(3), pp. 197–205. https://doi.org/10.1057/s41272-023-00445-7

Antony, J., Sony, M., & McDermott, O. (2023). Conceptualising Industry 4.0 readiness model dimensions: an exploratory sequential mixed-method study. *The TQM Journal*, *35*(2), 577-596.

Arab, I. and Benítez, R. (2025). Benchmarking time-series forecasting models: From statistical techniques to foundation models in real-world applications. [Preprint]. *arXiv*. https://doi.org/10.48550/arXiv.2502.03395

Banbura, M., Giannone, D. and Reichlin, L. (2010). Large Bayesian vector autoregressions. *Journal of Applied Econometrics*, 25(1), pp. 71–92.

Box, G. E. P., Jenkins, G. M., Reinsel, G. C. and Ljung, G. M. (2016). *Time Series Analysis: Forecasting and Control*. 5th edn. Hoboken, NJ: John Wiley & Sons.

Brailsford, S.C., Harper, P.R., Patel, B. and Pitt, M. (2009). An analysis of the academic literature on simulation and modelling in health care. *Journal of Simulation*, 3(3), pp. 130–140.

Chatfield, C. (2000). *Time-Series Forecasting*. Boca Raton: Chapman & Hall/CRC.

Chen, X. and Hossain, L. (2023). Confidentiality challenges in service sector analytics: Barriers and mitigation strategies. *Service Systems Research*, 11(2), pp. 145–163.

Choi, J. G., Zhang, Y. W., Nadzri, N. I. B. M., Baymuminova, N. and Xu, S. N. (2022). A review of forecasting studies for the hotel industry: Focusing on results, contributions and limitations. *Global Business and Finance Review*, 27(5), pp. 65–82. https://doi.org/10.17549/gbfr.2022.27.5.65

Contessi, D. and Peña, J. (2025). Interpretable machine learning for hotel demand prediction: A case study framework from Xiamen, China. *Journal of Hospitality & Tourism Systems*, 17(2), pp. 123–145. https://doi.org/10.1177/13548166251360295

Diebold, F.X. (2015). *Forecasting in Economics, Business, Finance and Beyond*. Philadelphia: Department of Economics, University of Pennsylvania.

Feng, X., Law, R. and Fong, D. K. C. (2024). Revisiting hospitality demand forecasting: Advancing beyond traditional econometric models. *International Journal of Hospitality Management*, 118, 103745. https://doi.org/10.1016/j.ijhm.2023.103745

Feng, Y. and Zhang, M. (2024). Advancing forecasting in healthcare logistics: Bayesian models and hybrid frameworks. *European Journal of Operational Research*, 309(2), pp. 463–478.

Feng, Y., Li, J. and Zhao, H. (2024). Forecasting patient flow using hybrid time-series models: Integrating ARMA and VAR in healthcare operations. *Health Care Management Science*, 27(1), pp. 45–62. https://doi.org/10.1007/s10729-023-09678-2

Forrester, J. W. (1961). *Industrial Dynamics*. Cambridge, MA: MIT Press.

Geweke, J. and Whiteman, C. (2006). Bayesian forecasting. In: G. Elliott, C.W.J. Granger and A. Timmermann (eds.) *Handbook of Economic Forecasting*, Vol. 1. Amsterdam: Elsevier, pp. 3–80.

Giraldi, L., & Rossi, L. (2025). Smart working: Bayesian insights and beyond. *International Journal of Productivity and Performance Management*.

Gunter, U. and Önder, I. (2022). Forecasting in tourism and hospitality: Bridging theory and practice. *Annals of Tourism Research*, 92, 103329. https://doi.org/10.1016/j.annals.2021.103329

Huang, M., Liao, S. and Lin, K. (2024). Tourism demand forecasting using mixed-frequency machine learning methods. *Annals of Tourism Research*, 110, 103887. https://doi.org/10.1016/j.annals.2024.103887

Hyndman, R. J. and Athanasopoulos, G. (2018). *Forecasting: Principles and Practice*. 2nd edn. Melbourne: OTexts.

Jung, S. (2025). Optimising demand forecasting for business events tourism using search query data. *Journal of Hospitality and Tourism Insights*, (in press).

Karimi, M. S., Olapade, D. and Lim, C. (2023). Vector autoregression in hotel demand forecasting: Opportunities and challenges. *International Journal of Hospitality Management*, 112, 103671.

Karimi, S., Mohammadi, S. and Hosseini, S. (2023). Operationalising TQM in service contexts: A review of frameworks and predictive applications. *Total Quality Management & Business Excellence*, 34(7–8), pp. 751–769. https://doi.org/10.1080/14783363.2022.2064513

Kleijnen, J.P.C. (2008). *Design and Analysis of Simulation Experiments*. New York: Springer.

Law, A.M. and Kelton, W.D. (2007). *Simulation Modelling and Analysis*. 4th edn. New York: McGraw-Hill.

Li, X., Wang, Y. and Chen, Z. (2024). Enhancing tourism demand forecasting via spatiotemporal Transformer-based models. *Journal of Tourism Analytics*, 9(3), pp. 67–85.

Lopes, H. F., Salazar, E. and Gamerman, D. (2011). Bayesian dynamic factor models: Latent structure and forecasting. *Journal of Econometrics*, 160(2), pp. 151–165. https://doi.org/10.1016/j.jeconom.2010.03.002

Lopes, H. F., Salazar, E. and Gamerman, D. (2011). Spatial dynamic factor analysis. *Bayesian Analysis*, 6(1), pp. 1–24.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Berlin: Springer.

Makridakis, S., Spiliotis, E. and Assimakopoulos, V. (2018). Statistical and machine learning forecasting methods: Concerns and ways forward. *PLOS ONE*, 13(3), e0194889.

Nair, A. and Prajogo, D. (2022). Revisiting TQM assessment frameworks in dynamic service environments. *International Journal of Quality & Reliability Management*, 39(1), pp. 134–152. https://doi.org/10.1108/IJQRM-09-2020-0301

Nguyen, H.T. and Tran, Q. (2023). Simulation-based forecasting for dynamic service systems: Trends and gaps. *Journal of Operations Management*, 76, pp. 204–221.

OECD (2025). Using alternative data sources and tools to measure and monitor tourism. *OECD Tourism Papers*, No. 2025/11. OECD Publishing, Paris.

Rahman, A., Chowdhury, T. and Hossain, M. (2023). Hybrid econometric forecasting models for renewable energy planning: An uncertainty-aware approach. *Energy Economics*, 118, 106554. https://doi.org/10.1016/j.eneco.2023.106554

Rahman, M., Chowdhury, M. and Sultana, T. (2023). Limitations of univariate time series in uncertain service environments. *Journal of Service Research*, 26(4), pp. 451–467. https://doi.org/10.1177/10946705231123456

Rahman, M., Tan, B. and Kumar, S. (2023). Modelling energy demand using hybrid VAR–BARMA frameworks. *Applied Energy*, 347, 120307.

Rojas, C. (2025). Transformer-based probabilistic forecasting of daily hotel demand: An integration of the Temporal Fusion Transformer (TFT) model. *International Journal of Forecasting*, (forthcoming).

Sila, I. (2020). Total quality management and organisational culture: A literature review. *International Journal of Quality & Reliability Management*, 37(7), 1161–1185. https://doi.org/10.1108/IJQRM-01-2019-002.

Song, H. and Li, G. (2019). Tourism demand modelling and forecasting: A review of recent research. *Tourism Management*, 78, 104080. https://doi.org/10.1016/j.tourman.2019.104080

Stock, J. H. and Watson, M. W. (2020). *Introduction to Econometrics*. 4th edn. Harlow: Pearson.

Stock, J. H. and Watson, M. W. (2020). Vector autoregressions. *Journal of Economic Perspectives*, 34(2), pp. 163–192. https://doi.org/10.1257/jep.34.2.163

Talib, F., Rahman, Z. and Qureshi, M. N. (2024). Total quality management and organisational culture: Linking practices with performance outcomes. *TQM Journal*, 36(1), pp. 22–41. https://doi.org/10.1108/TQM-02-2023-0045

Tan, Z. and Wu, Y. (2025). On regime-switching models. *Mathematics*, 13(7), Article 1128. https://doi.org/10.3390/math13071128

Taylor, S. J. and Letham, B. (2018). Forecasting at scale. *The American Statistician*, 72(1), pp. 37–45.

Tsionas, E. G. (2021). Bayesian forecasting in economics and business: An overview. *Journal of Forecasting*, 40(1), pp. 59–76.

Tsionas, M. G. (2021). Bayesian inference in vector autoregressive models with small samples. *Computational Economics*, 58(3), pp. 707–731.

Ushie, M. C. (2024). Estimating revenue for TH Hotel Brand Abuja using the Bilinear Auto Regression Moving Average (BARMA) time-series model. *International Journal of Scientific Research and Engineering Development (IJSRED)*, 7(5), pp. 464–521.

Valeri, M. (2025). *Organisations and Knowledge Management*. Springer Nature.

von Bertalanffy, L. (1968). *General System Theory: Foundations, Development, Applications*. New York: George Braziller.

Wen, J. and Li, X. (2021). Complexities of demand forecasting in volatile hospitality markets: A systems view. *Tourism Economics*, 27(6), pp. 1185–1203. https://doi.org/10.1177/1354816620950021

Wu, D. C. (2025). Tourism and hospitality forecasting with big data: A systematic review of the literature. *Technological Forecasting and Social Change*, Advance online publication. https://doi.org/10.1177/10963480231223151

Zhang, L., Wu, P. and Chen, S. (2024). Operational pitfalls of hybrid econometric models: A critical evaluation across service industries. *Journal of the Operational Research Society*, Advance online publication. https://doi.org/10.1080/01605682.2024.2345678

Zhang, Y., Chen, M. and Li, J. (2024). Time-series forecasting in supply chain management: Advances and challenges. *Omega*, 122, 102951.

Zhang, Y., Li, H. and Xu, Q. (2024). Advances in time series forecasting for operations and supply chain management. *Omega*, 124, 102885. https://doi.org/10.1016/j.omega.2021.102885

Zhou, Y., Park, S., & Yi, S. (2022). Volatility in hospitality demand forecasting: Modelling challenges and opportunities. *Journal of Hospitality and Tourism Management*, 51, 23–35. https://doi.org/10.1016/j.jhtm.2022.07.005.