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Bayesian Quality Control Models for Decision-Making Under Uncertainty

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Abstract. This review examines Bayesian quality control as a framework for decision-making under these conditions. It synthesizes its inferential and decision-theoretic foundations; reviews Bayesian control charts, hierarchical models, process-capability analysis, sequential updating, Bayesian networks, and computational methods; and examines applications in real-time monitoring, quality prediction, small-sample and high-mix production, predictive maintenance and reliability, and Lean Six Sigma. Across these applications, Bayesian models represent uncertainty through posterior and predictive distributions, allowing quality teams to update estimates as sensor, inspection, or failure data accumulate. This is particularly relevant when production volumes are low, evidence comes from several sources, or decisions depend on the probability of a shift, nonconformance, or reliability shortfall. The review also finds that Bayesian methods complement established quality practices: they can extend control charts, capability assessment, and continuous-improvement work by making uncertainty explicit. Their practical value, however, depends on more than inference. Computational demand can delay online decisions; weakly grounded priors can influence posterior conclusions; probabilistic outputs can be difficult to interpret; and legacy data systems, application-specific methods, and absent benchmarking standards limit transfer across manufacturing settings.

Keywords: Bayesian quality control; Manufacturing; Uncertainty Quantification; Bayesian Networks; Statistical Process Control

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A. INTRODUCTION

Quality control in manufacturing has long depended on frequentist statistical methods, including control charts, hypothesis testing, and process capability analysis. These methods treat process parameters as fixed quantities and often require large sample sizes to produce reliable estimates (Kargar et al., 2013). Statistical process control (SPC) remains a critical quality management tool across industries, relying on data collection, analysis, and interpretation to identify variations and trends within production processes (Nwamekwe et al., 2025h). Process capability indices, for instance, have been widely adopted in manufacturing to measure whether a process reproduces items that meet preset quality requirements (Igbokwe et al., 2025b). While these tools perform well in stable, high-volume production settings, they face clear limitations in modern manufacturing systems where uncertainty, variability, and limited data availability are common (Nannapaneni et al., 2020; Igbokwe et al., 2025). Manufacturing environments today involve multiple interacting subsystems, each contributing distinct sources of uncertainty, including input variability, process noise, modelling errors, and measurement imprecision (Nannapaneni et al., 2020; Vitalis et al., 2024). In such contexts, frequentist approaches struggle to adapt quickly or to incorporate prior knowledge about process behaviour (Nwamekwe et al., 2020; Sun et al., 2024).

Bayesian methods offer a probabilistic framework that addresses many of these shortcomings. At its core, Bayesian inference applies Bayes' theorem to update prior beliefs about model parameters as new data become available, producing posterior distributions that reflect both existing knowledge and observed evidence (Dong et al., 2023; Shi et al., 2024; Igbokwe & Nwamekwe, 2025). This updating mechanism is particularly valuable in settings where data are sparse, noisy, or evolving over time (Walker et al., 2024; Chidiebube et al., 2025; Sun et al., 2024). For example, in ceramics manufacturing, Nwamekwe et al. (2026c) demonstrated how a Bayesian approach reduces uncertainty in flexural strength estimates from a fixed 15% to a range between 8.3% and 13.4% as new experimental data are incorporated. Similarly, Dong et al. (2023) showed that Bayesian inference enables transparent communication and systematic updating of model uncertainty in material flow analysis, with the speed advantage that newly acquired data require only the previous posterior as a starting point rather than a full reanalysis. In pharmaceutical processes, Bayesian inference has been recognized for its ability to describe variability with limited samples by incorporating prior knowledge and updating parameters as new data arrive (Chidiebube et al., 2025a). Sun et al. (2024) applied Bayesian statistical methods to predict carburizing-induced dimensional changes in torsion bars, establishing posterior and predictive distribution models that integrate prior knowledge with real-time measurement data. These examples illustrate the broad applicability of Bayesian methods across manufacturing domains, from materials science to process monitoring, and their capacity to support continuous learning and adaptation in quality control.

Problem Framing

Manufacturing systems operate under multiple, interacting sources of uncertainty. These include variability in input material properties, process parameter fluctuations, environmental disturbances, measurement noise, and modelling errors (Igbokwe et al., 2025; Nannapaneni et al., 2020; Shi et al., 2024). Shi et al. (2024) noted that uncertainty exists widely in manufacturing, from traditional to intelligent systems, and that the complexity of manufacturing scenarios is increasing with the integration of rapidly developing intelligent technology. Nannapaneni et al. (2020) identified specific uncertainty sources in cyber-physical manufacturing processes, including resource and communication uncertainty from the computing subsystem, input uncertainty and process variability from the manufacturing process itself, and measurement uncertainty from sensors. These uncertainty sources aggregate and compound over time due to continuous interactions between subsystems (Nannapaneni et al., 2020).

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Traditional quality control methods often treat these uncertainties implicitly or ignore them altogether. Frequentist control charts, for instance, monitor process variance but do not provide a unified mechanism for fusing heterogeneous information or calibrating uncertain parameters (Igbokwe et al., 2024; Vitalis et al., 2024). This limitation leads to delayed detection of process shifts and suboptimal decision-making. Kargar et al. (2013) observed that most existing research on process capability has used traditional frequency methods based on single samples, which do not allow for dynamic updating of parameter estimates. Nwamekwe et al. (2026a) similarly noted that classical control charts lack the capacity to incorporate prior knowledge of process parameter distributions, which limits their effectiveness in handling parametric uncertainty.

Bayesian quality control models address these gaps by representing uncertainty explicitly through probability distributions. The posterior distribution, obtained by combining a prior distribution with observed data through the likelihood function, reflects both prior beliefs and empirical evidence (Dong et al., 2023; Shi et al., 2024; Whalen et al., 2021). Okeagu et al. (2024) proposed a systematic framework using Bayesian networks to aggregate uncertainty from multiple sources for performance prediction in manufacturing, enabling sensitivity analysis, dimension reduction, model calibration, and forward uncertainty propagation within a single probabilistic structure. Their later work (Nannapaneni et al., 2020) extended this to a dynamic Bayesian network approach for online monitoring and control, where sensor data continuously update process parameters and predictive models guide control actions. Nwamekwe and Okpala, (2026) developed a dynamic Bayesian reliability estimation and control method for industrial products under failure trials, where the estimated reliability is updated using point estimates with each new data source. The Bayesian adaptive EWMA control chart proposed by Nwamekwe et al. (2025i) demonstrated superior performance in detecting out-of-control signals in semiconductor manufacturing by combining prior information with sample data through posterior and posterior predictive distributions. Labha et al. (2025) introduced a Bayesian EWMA control chart for monitoring the shape parameter of lifetime Pareto distribution processes, showing that the Bayesian chart is more effective in handling parameter uncertainty and detecting small process shifts compared to classical alternatives.

Despite these theoretical and demonstrated advantages, practical adoption of Bayesian quality control models remains limited. Computational complexity is a persistent barrier, as Bayesian inference often relies on sampling-based methods such as Markov Chain Monte Carlo (MCMC), which are computationally expensive, especially as the number of uncertain parameters increases (Nannapaneni et al., 2020; Vitalis et al., 2024; Shi et al., 2024). Okpala et al. (2024) noted that prediction or inference in Bayesian networks is computationally expensive because it is mostly sampling-based, although analytical estimation is possible in special cases. Nannapaneni et al. (2020) addressed this by applying variance-based global sensitivity analysis for dimension reduction to facilitate real-time analysis. The lack of standardized frameworks for representing and exchanging Bayesian models also hinders adoption. onyeka et al. (2024) developed a Predictive Model Markup Language (PMML) representation for Bayesian networks to aid in their communication and exchange, recognizing that standardization is necessary for broader deployment. Shi et al. (2024) proposed a meta-model architecture and uncertainty quantification framework to guide reliable process execution, noting that post-decision methods alone cannot fully meet the reliability needs of modern manufacturing.

Objective of the Review

This review synthesizes Bayesian quality control models for decision-making under uncertainty in manufacturing. It examines the range of modelling approaches that have been proposed, from Bayesian networks for multi-source uncertainty aggregation to dynamic Bayesian networks for online monitoring and control to Bayesian control charts for process monitoring and to Bayesian inference for parameter estimation and reliability updating. The

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review covers inference techniques, including MCMC sampling, variational methods, and approximate approaches, as well as strategies for prior elicitation, such as expert-based methods and informative priors derived from historical data. Application strategies span diverse manufacturing contexts, including semiconductor manufacturing, additive manufacturing, machining processes, materials characterization and pharmaceutical processes. The review also identifies persistent challenges related to computational efficiency in real-time settings, interpretability of posterior distributions for practitioners, and the integration of Bayesian models with emerging digital manufacturing infrastructure. By bringing together these threads, the review aims to provide a coherent assessment of the current state of Bayesian quality control and to identify directions for future research and practical implementation.

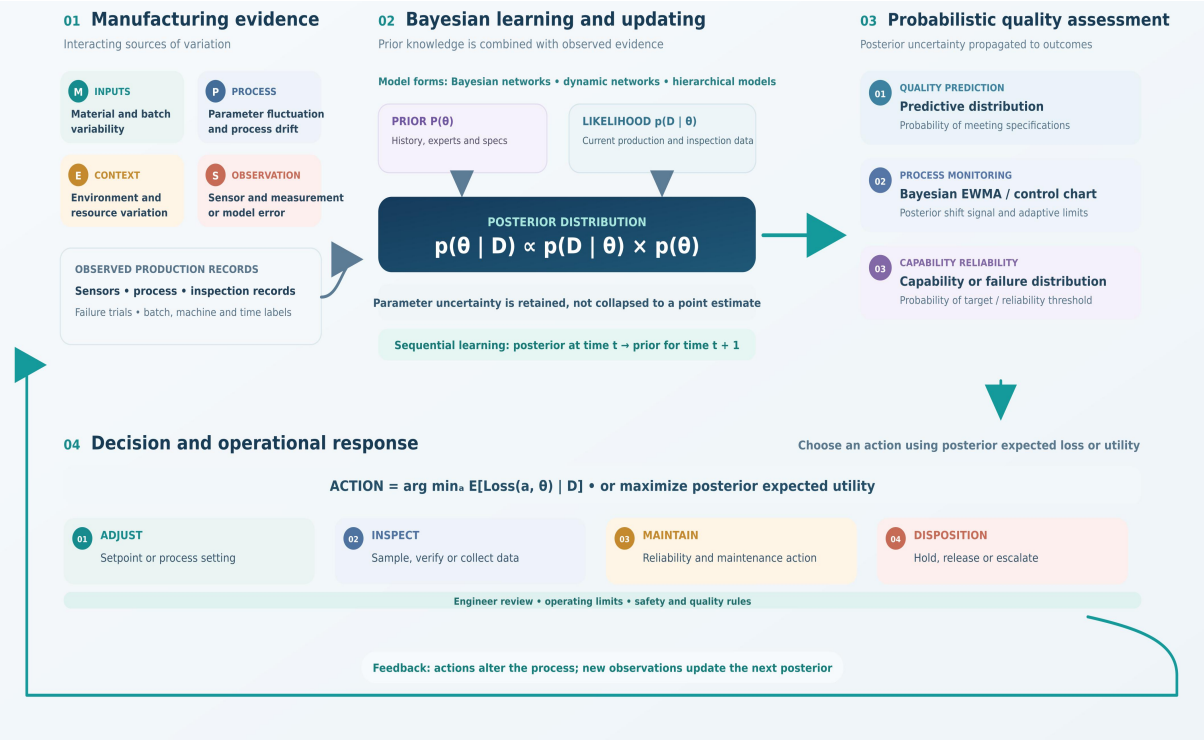


Figure 1: Conceptual Framework for Bayesian Quality Control in Uncertain Manufacturing Environments

B. LITERATURE REVIEW

Bayesian Inference Principles

Bayesian inference rests on a simple but consequential idea: prior beliefs about unknown parameters are updated with observed data to produce posterior distributions. The core relationship is expressed through Bayes' theorem, where the posterior probability of a parameter given data equals the product of the likelihood of the data given the parameter and the prior probability of the parameter, divided by the marginal probability of the data (Igbokwe et al., 2025b; Chidiebube et al., 2025; Igbokwe & Nwamekwe, 2025). In formal terms, , where θ represents the model parameters and D represents the observed data. The prior distribution P(θ) encodes existing knowledge or assumptions about the parameter before any data are observed. The likelihood captures how probable the observed data are under different parameter values. The posterior then reflects the updated state of knowledge after incorporating the data (Shi et al., 2024; Chidiebube et al., 2025a). This updating mechanism is sequential in nature. Dong et al. (2023) emphasized a key practical advantage:

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once a posterior distribution has been obtained from one round of data, it serves as the prior for the next round, so newly acquired data require only the previous posterior as a starting point rather than a full reanalysis. Nwamekwe et al. (2025g) demonstrated this sequential updating in the context of flexural strength estimation for silicon carbide, where the posterior distribution was refined as additional experimental data became available, reducing uncertainty from a fixed 15% to a range between 8.3% and 13.4%. In pharmaceutical process modelling, Dong et al. (2023) noted the capacity of Bayesian inference to describe variability with limited samples by incorporating prior knowledge and updating parameters as new data arrive. Whalen et al. (2021) applied Bayesian inference to predict distributions for model input parameters in additive manufacturing, using experimental results to update prior assumptions about laser absorptivity and powder bed porosity. The strength of the Bayesian framework lies in its explicit treatment of uncertainty at every stage of the inference process, from the specification of priors to the interpretation of posteriors (Igbokwe et al., 2025; Shi et al., 2024).

Comparison with Frequentist Approaches

Frequentist and Bayesian methods differ in how they treat unknown parameters. Frequentist methods estimate parameters as fixed, unknown constants and rely on the long-run frequency properties of estimators and test statistics (Igbokwe et al., 2025b; Wang et al., 2023). Confidence intervals, p-values, and hypothesis tests are the standard tools. These methods require repeated sampling assumptions and often need large sample sizes to produce reliable estimates (Nwamekwe et al., 2026). Bayesian methods, by contrast, treat parameters as random variables described by probability distributions (Dong et al., 2023; Shi et al., 2024). This distinction has direct consequences for quality control. Igbokwe et al. (2025b) observed the limitations of traditional frequency methods based on single samples for assessing process capability, noting the inability to incorporate prior information or update estimates dynamically. Nwamekwe et al. (2026a) pointed out the inability of classical control charts to incorporate prior knowledge of process parameter distributions, which limits their effectiveness in handling parametric uncertainty. Labha et al. (2025) compared Bayesian and classical EWMA control charts for monitoring the shape parameter of a Pareto distribution process and found the Bayesian chart more effective in detecting small process shifts and handling parameter uncertainty. The Bayesian approach provides a full posterior distribution for each parameter, which conveys richer information than a single point estimate or confidence interval (Ezeanyim et al., 2026; Walker et al., 2024). For instance, Whalen et al. (2021) showed how posterior distributions for absorptivity and porosity in additive manufacturing captured the dependence of these parameters on laser power, a relationship not easily expressed through frequentist point estimates. Nwamekwe and Edokpia (2026a) used Bayesian updating to dynamically estimate product reliability under failure trials, where each new data source refined the reliability estimate in a way not possible with fixed-parameter methods. The Bayesian framework also handles small sample sizes more naturally because the prior distribution regularizes the inference when data are sparse (Kargar et al., 2013; Sun et al., 2024; Okpala et al., 2025a).

Sources of Uncertainty in Quality Control

Uncertainty in manufacturing processes arises from multiple, interacting sources. Nannapaneni et al. (2020) identified specific categories of uncertainty in cyber-physical manufacturing: resource and communication uncertainty from the computing subsystem, input uncertainty and process variability from the manufacturing process itself, and measurement uncertainty from sensors. Shi et al. (2024) provided a broader classification, noting the presence of uncertainty across traditional and intelligent manufacturing systems and emphasizing the increasing complexity introduced by the integration of intelligent technology. Process variability refers to the inherent randomness in process outputs, even when all controllable factors are held constant (Igbokwe et al., 2024; Shi et al., 2024). Measurement errors arise from sensor imprecision, calibration drift, and environmental

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interference (Nannapaneni et al., 2020; Papananias et al., 2022). Nwamekwe and Igbokwe (2024) addressed measurement uncertainty in multistage manufacturing by developing a probabilistic framework for product health monitoring, where on-machine measurements carry their own uncertainty and must be fused with process model predictions. Environmental conditions, including temperature, humidity, and vibration, introduce additional variability not always captured by process models (Nannapaneni et al., 2020; Sun et al., 2024). Sun et al. (2024) studied carburizing-induced dimensional changes in torsion bars and found the need to account for variability in heat treatment conditions when predicting distortion patterns. Limited sample sizes represent another important source of uncertainty, particularly in low-volume or early-stage production (Kargar et al., 2013; Nwamekwe et al., 2026c). Walker et al. (2024) showed how uncertainty in flexural strength estimates remained high when data were scarce and decreased as more experimental observations were incorporated through Bayesian updating. Nannapaneni et al. (2020) further noted the compounding effect: because the computing subsystem, the manufacturing process, and the sensor system interact continuously, uncertainty sources aggregate over time. Modelling errors add yet another layer, as the mathematical models used to predict process behaviour are themselves approximations of reality (Igbokwe et al., 2024; Nwamekwe et al., 2025f). Ezeanyim et al. (2026) addressed this by using Bayesian inference to calibrate model parameters and propagate uncertainty through the Eagar-Tsai model for melt pool geometry prediction, acknowledging the gap between model assumptions and physical behaviour.

Bayesian Representation of Process Parameters

In Bayesian quality control, process parameters such as the process mean, variance, and capability indices are represented as probability distributions rather than fixed values (Kargar et al., 2013; Chidiebube et al., 2025b; Okpala et al., 2025). This representation allows for dynamic updating as new data are collected. Igbokwe et al. (2025b) used an informative normal prior distribution for the process capability index and derived the posterior distribution by combining the prior with observed subsamples, enabling a probabilistic assessment of whether the process meets capability requirements. Nwamekwe and Okpala, (2026) modelled product reliability as a distribution updated through Bayesian inference each time new failure trial data became available. The posterior distribution of reliability was then used to construct confidence intervals for monitoring and control. Sun et al. (2024) established posterior and predictive distribution models for torsion bar dimensions, integrating prior knowledge about carburizing behaviour with real-time measurement data to predict expansion patterns. In additive manufacturing, Whalen et al. (2021) represented laser absorptivity and powder bed porosity as distributions inferred from experimental data, then propagated these distributions through a physics-based model using Monte Carlo methods to estimate melt pool depth and its associated uncertainty. Dong et al. (2023) applied expert elicitation to generate informative prior distributions for material flow parameters, which were then updated through Bayesian inference with data from the United States Geological Survey and the World Steel Association. The results showed a reduction in parametric uncertainty when incorporating collected data. Nwamekwe and Igbokwe (2024) used Gaussian Process Regression models to produce probabilistic predictions of product quality, where the output is a probability density function for the measurand of interest rather than a single deterministic value. This distributional representation supports the computation of conformance and non-conformance probabilities given tolerance specifications (Papananias et al., 2022). The ability to represent parameters as distributions is what enables Bayesian models to propagate uncertainty through the entire decision chain, from parameter estimation to process prediction to quality assessment (Okeagu et al., 2024; Shi et al., 2024).

Decision-Theoretic Framework

Bayesian decision-making integrates probability distributions with loss functions and expected utility to guide quality control actions. The core principle is to select the action minimizing expected loss or maximizing expected utility, where the expectation is taken over

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the posterior distribution of the uncertain parameters (Wang et al., 2023; Ezeanyim et al., 2025). Nwamekwe et al. (2025i) developed a Bayesian Adaptive EWMA control chart built on diverse loss functions, including the Square Error Loss Function (SELF) and the Linex Loss Function (LLF). The choice of loss function directly affects the Bayesian estimates and the sensitivity of the control chart to different types of process shifts (Nwamekwe et al., 2026a; Emeka et al., 2025a). Labha et al. (2025) introduced a Bayesian EWMA control chart for monitoring the shape parameter of a Pareto distribution process, where Bayesian estimates were calculated under different loss functions and the chart's performance was evaluated using Average Run Length (ARL) and Standard Deviation of Run Length (SDRL) through Monte Carlo simulations. The results indicated the Bayesian chart's superior performance in detecting small process shifts compared to the classical alternative. Nwamekwe and Edokpia, (2026a) presented a reliability control method where the lower limit of the confidence interval of the reliability distribution is maintained above a control limit, triggering quality-assurance actions when the interval falls below the threshold. This approach directly links the posterior distribution to a decision rule with practical consequences. Okeagu et al. (2024) proposed a framework where Bayesian network predictions support sensitivity analysis and model calibration, enabling decision-makers to identify the most influential uncertainty sources and allocate resources accordingly. Nannapaneni et al. (2020) extended this to a predictive control framework where control actions are implemented after predicting the state of the manufacturing process at a future time, with the prediction accounting for aggregated uncertainty from multiple sources. The decision-theoretic framework thus connects the statistical inference to the operational response, ensuring quality control decisions reflect the full state of knowledge about the process and its uncertainties (Wang et al., 2023; Okeagu et al., 2024; Okpala et al., 2025; Ezeanyim et al., 2025a).

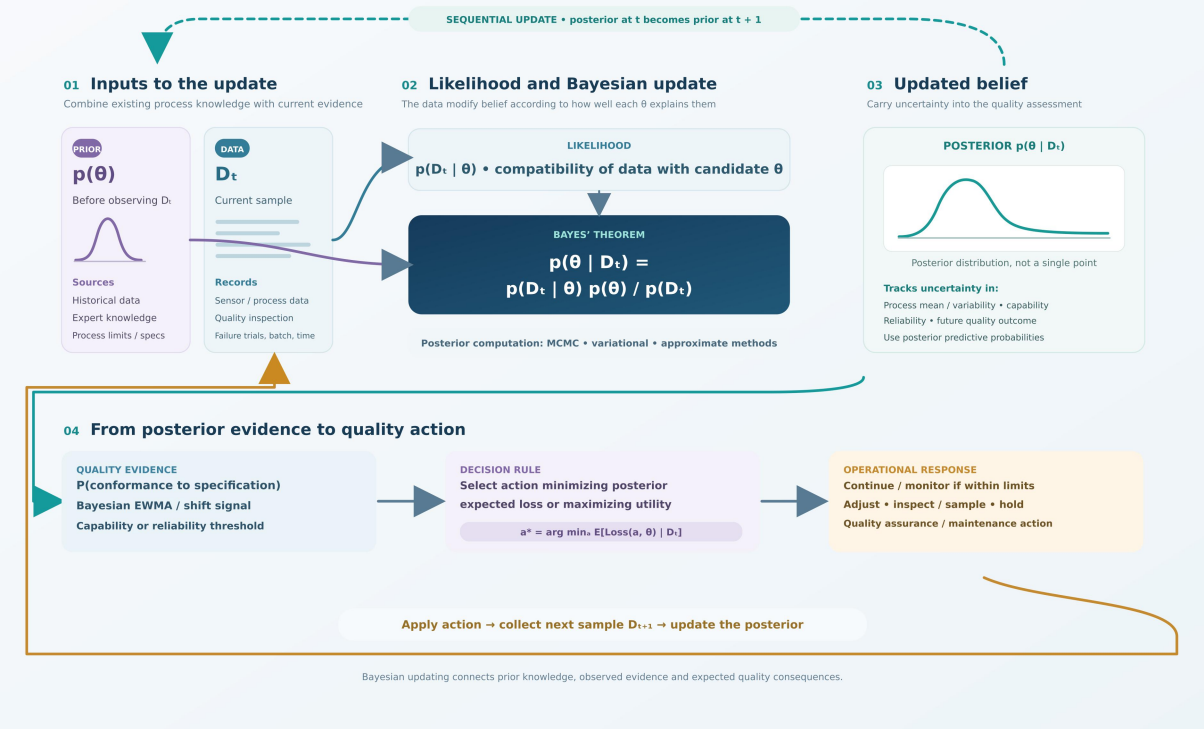


Figure 2: Bayesian Updating Process for Quality Control Decision-Making

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C. RESEARCH METHODOLOGY

Computational Techniques

Bayesian inference requires computing posterior distributions, which is often analytically intractable for realistic models. Two broad families of computational methods address this challenge: sampling-based methods and optimization-based approximations (Nannapaneni et al., 2020; Onyeka and Emeka, 2025; Lian et al., 2021). Markov Chain Monte Carlo (MCMC) methods, including Gibbs sampling and Hamiltonian Monte Carlo (HMC), are the most widely used sampling approaches. MCMC generates samples from the posterior distribution by constructing a Markov chain whose stationary distribution matches the target posterior (Shi et al., 2024; Baranowski, 2022; Igbokwe et al., 2025a). Baranowski (2022) applied Hamiltonian Monte Carlo for multilevel hierarchical Bayesian models of IoT device failures, noting the computational efficiency of non-centered parameterization in the HMC framework. Igbokwe et al. (2025a) used HMC with a No-U-Turn Sampler (NUTS) for a hierarchical Bernoulli mixture model, monitoring convergence through diagnostic plots and CODA diagnostics to ensure the MCMC process reached equilibrium (Igbokwe et al., 2025a). Yang et al. (2018) noted that the successful application of MCMC methods in Bayesian inference has extended the choice of prior distributions beyond conjugate families, significantly broadening the scope of models that are computationally feasible. Onyeka et al. (2024) observed that prediction or inference in Bayesian networks is computationally expensive because it is mostly sampling-based, although analytical estimation is possible in special cases involving discrete or Gaussian variables. Nannapaneni et al. (2020) addressed the computational burden for real-time applications by applying variance-based global sensitivity analysis for dimension reduction, reducing the number of uncertain parameters that need to be estimated from sensor data. Variational inference offers an alternative to MCMC by approximating the posterior distribution with a simpler distribution and optimizing the approximation through minimization of the Kullback-Leibler divergence (Emeka et al., 2025). Lian et al. (2021) proposed a variational Bayesian structural time-series model for fuel sales forecasting, noting that variational inference does not achieve higher computing speed than MCMC in all cases but produces posterior inference results approximate to those obtained by MCMC, with the advantage of being more scalable to large datasets. The choice between MCMC and variational inference involves a trade-off between accuracy and computational cost. MCMC provides asymptotically exact samples from the posterior but is computationally expensive, especially as the number of parameters increases (Nannapaneni et al., 2020; Onyeka and Emeka, 2025; Shi et al., 2024). Variational inference is faster and more scalable but introduces approximation error (Emeka et al., 2025). For real-time quality control applications, the computational cost of inference is a practical constraint that shapes the choice of method and the feasibility of online implementation (Nannapaneni et al., 2020; Okpala et al., 2024a).

D. RESULTS AND DISCUSSION

Real-Time Process Monitoring

Bayesian models support continuous monitoring of manufacturing processes by updating parameter estimates as new sensor data arrive, enabling early detection of process shifts before defective products accumulate. Nannapaneni et al. (2020) developed a dynamic Bayesian network approach for online monitoring and control of a cyber-physical turning process, where sensor data continuously update process parameters and predictive models guide control actions in real time. Their framework accounts for uncertainty sources from the computing subsystem, the manufacturing process, and sensors, all of which aggregate and compound over time due to continuous interactions between subsystems (Nannapaneni et al., 2020). To address the computational burden of real-time parameter estimation, they

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applied variance-based global sensitivity analysis for dimension reduction, reducing the number of uncertain parameters that need updating at each time step (Nannapaneni et al., 2020). Papananias et al. (2022) presented a probabilistic framework for product health monitoring in multistage manufacturing, where predictions of dimensional quality are updated with subsequent measurements, including on-machine measurements, in an online incremental learning fashion. Their system uses Bayesian information fusion to update the conditional probability distribution of end product quality as new information becomes available, achieving an average accuracy better than 5 micrometres in terms of root mean squared error for diameter deviation prediction (Nwamekwe & Nwabunwanne, 2025). Wang et al. (2023) demonstrated a Bayesian Adaptive EWMA control chart applied to semiconductor manufacturing, where the chart incorporates prior information through posterior and posterior predictive distributions and detects out-of-control signals more effectively than classical charts based on simple random sampling. Vanli (2013) proposed a Bayesian change-point method for monitoring processes regulated with proportional-integral controllers, fitting an exponential rise model to control input actions in response to a step shift. Simulation studies showed this method had better run-length performance in detecting step shifts than the Shewhart chart on individuals and special-cause charts on residuals of time series models (Vanli, 2013). Nwamekwe et al. (2025e) introduced a Bayesian EWMA control chart for monitoring the shape parameter of a Pareto distribution process, with results indicating superior performance in detecting small process shifts compared to the classical EWMA chart. These applications share a common principle: the posterior distribution is updated sequentially, and control decisions are triggered when the updated distribution signals a departure from the in-control state. This approach reduces detection delay and supports timely corrective action.

Quality Prediction and Forecasting

Probabilistic models predict future quality performance under uncertainty by propagating parameter distributions through process models to generate predictive distributions for quality outcomes. Whalen et al. (2021) applied Bayesian inference to predict distributions for the input parameters of the Eagar-Tsai model for melt pool geometry in additive manufacturing of 316L stainless steel. They used Monte Carlo uncertainty propagation with the inferred parameter distributions to estimate melt pool depth and its associated uncertainty, and constructed a printability map based on power-dependent input parameter values (Ezeanyim et al., 2026). The Bayesian approach improved the accuracy of predicting keyhole regions in the laser power-scan speed parameter space compared to deterministic methods (Nwamekwe et al., 2025f). Sun et al. (2024) established posterior and predictive distribution models for torsion bar dimensions under carburizing heat treatment, integrating prior knowledge with real-time measurement data to predict expansion behaviour. Their Bayesian approach improved the precision of dimensional predictions and contributed to optimizing the manufacturing process (Sun et al., 2024). Igbokwe et al. (2025) proposed a framework using Bayesian networks to aggregate uncertainty from multiple sources for the prediction of energy consumption in manufacturing, one of the key metrics of manufacturing process sustainability performance. Their approach supports forward uncertainty propagation, where the uncertainty in input variables and model parameters is propagated through the network to produce a distribution over the predicted output (Vitalis et al., 2024). Papananias et al. (2022) used Gaussian Process Regression models to produce probabilistic predictions of product quality in multistage manufacturing, where the output is a probability density function for the measurand of interest. Having obtained this distribution, they computed conformance and non-conformance probabilities given tolerance specifications, supporting the principle of inspection by exception (Nwamekwe & Nwabunwanne, 2025). Dong et al. (2023) reviewed data-driven modelling methods for pharmaceutical processes and noted the capacity of Bayesian inference to describe variability with limited samples, enabling more reliable predictions of process outcomes when data are scarce (Dong et al., 2023). These

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examples show how Bayesian quality prediction moves beyond single-point forecasts to provide distributional assessments that communicate the range and likelihood of future quality outcomes.

Small-Sample and Low-Volume Production

Bayesian methods are particularly effective in manufacturing environments where data are limited, because the prior distribution regularizes inference and compensates for small sample sizes. Takada et al. (2023) proposed multivariate hierarchical Bayesian control charts for high-mix low-volume production, where obtaining sufficient measurement values for each product type is difficult. By setting multiple similar parameters to follow the same distribution using hierarchical priors, estimation accuracy improved even with few observations per product type, and the proposed method outperformed the Hotelling T-squared control chart in simulation analysis (Takada et al., 2023). Kargar et al. (2013) developed a Bayesian approach to capability testing based on the Cpk index using multiple subsamples, employing an informative normal prior distribution to derive the posterior distribution of the capability index. This approach enables probabilistic assessment of process capability even when the number of available samples is small (Nwamekwe et al., 2026b). Walker et al. (2024) demonstrated a Bayesian method to update uncertainty in the flexural strength of silicon carbide, where the uncertainty decreased from a constant 15% to a range between 8.3% and 13.4% as new experimental data were incorporated. Their approach showed how even a modest number of additional observations substantially reduces parametric uncertainty when combined with a well-specified prior (Nwamekwe et al., 2026c). Schach et al. (2025) introduced a hierarchical Bayesian model for meta-analysis of process variance in biopharmaceutical manufacturing, where determining process variances is challenging due to limited data availability. Their model integrates data from multiple products to provide more reliable estimates of critical quality attributes and enables prediction of cross-product variance applicable to new drug products (Schach et al., 2025). Dong et al. (2023) noted the capacity of Bayesian inference in pharmaceutical processes to describe variability with limited samples by incorporating prior knowledge and updating parameters as new data arrive. These applications demonstrate a consistent pattern: when data are scarce, the Bayesian framework draws on prior information and hierarchical structures to produce more stable and informative estimates than frequentist methods operating on the same limited data.

Predictive Maintenance and Reliability Analysis

Bayesian models estimate failure probabilities and support maintenance decisions by treating reliability parameters as distributions that are updated as operational data accumulate. Igbokwe et al. (2024a) proposed a dynamic Bayesian reliability estimation and control method for industrial products under failure trials. In their framework, the failure trial is performed at different operational time points, providing the sole data source for evaluating product status. The estimated reliability is updated using a point estimate each time new failure trial data become available, and a reliability control method monitors the confidence interval of the reliability distribution (Okpala et al., 2024). When the lower limit of the confidence interval falls below a control limit, a quality-assurance action is triggered (Nwamekwe & Okpala, 2026). They demonstrated this approach on a case of light-emitting diodes under failure trials at the production process, with results indicating the effectiveness of the estimation and control model (Okeagu et al., 2024). Yang et al. (2018) proposed a Bayesian-based reliability framework for a satellite-equipped harmonic gear drive, addressing the aggregation of multilevel system information and multisource data fusion in a hierarchical structure. Their approach classifies heterogeneous datasets into collections of statistical data, time-correlated data, and performance test data, and improves the estimation result for the whole system by fusing all available information throughout the system (Yang et al., 2018). Baranowski (2022) applied multilevel hierarchical Bayesian models to predict failures in IoT device populations, proposing data fusion of happenstance observations such

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as resets and failures to better estimate device parameters. The hierarchical model exhibited robustness to small amounts of data, and the Bayesian workflow allowed model diagnostics and tuning to assure computational fidelity (Baranowski, 2022). Nannapaneni et al. (2020) developed a predictive control framework for cyber-physical manufacturing where control actions are implemented after predicting the state of the manufacturing process at a future time, with the prediction accounting for aggregated uncertainty from multiple sources including sensor degradation and process drift. These applications show how Bayesian reliability analysis provides a principled mechanism for combining prior engineering knowledge with operational data to produce updated failure probability estimates that directly inform maintenance scheduling and quality-assurance decisions.

Integration with Lean and Six Sigma

Bayesian approaches enhance traditional Lean and Six Sigma methodologies by incorporating uncertainty directly into the decision-making process, rather than relying solely on point estimates and fixed thresholds. Lean and Six Sigma programs depend heavily on process capability analysis, control charts, and hypothesis testing to drive improvement decisions. Kargar et al. (2013) demonstrated how Bayesian process capability analysis provides a posterior probability that the process meets capability requirements, rather than a single Cpk value with an associated confidence interval. This probabilistic assessment gives practitioners a more complete picture of process performance and supports more informed decisions about whether to accept, adjust, or investigate a process (Igbokwe et al., 2025b). Wang et al. (2023) showed how a Bayesian Adaptive EWMA control chart, built on diverse loss functions, improves the detection of process mean shifts in semiconductor manufacturing compared to classical control charts. The incorporation of prior information through posterior and posterior predictive distributions aligns with the Six Sigma emphasis on data-driven decision-making while adding a layer of uncertainty quantification absent from conventional tools (Wang et al., 2023). Labha et al. (2025) introduced a Bayesian EWMA control chart for monitoring the shape parameter of a Pareto distribution process, noting the use of prior data and expert opinion to extract the prior predictive distribution and elicit hyperparameters. This approach provides a comprehensive Bayesian framework for process monitoring with practical flexibility in real-world scenarios (Ezeanyim et al., 2025a). Shi et al. (2024) proposed a meta-model architecture and uncertainty quantification framework for uncertainty modelling in manufacturing, arguing the need for pre-elimination of uncertainty to ensure the reliability of process execution. Their approach constructs a deterministic model to guide and drive the process, achieving the purpose of controlling uncertainty in advance (Shi et al., 2024). Igbokwe et al. (2024) proposed a Bayesian network framework for performance evaluation of manufacturing processes, where sensitivity analysis identifies the most influential uncertainty sources and guides resource allocation for process improvement. These contributions show how Bayesian methods complement Lean and Six Sigma by providing a formal mechanism for quantifying and communicating uncertainty in the metrics and decisions that drive continuous improvement programs.

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Figure 4: Application Domains of Bayesian Quality Control Models in Industrial Systems

Computational Complexity

Bayesian models impose a significant computational burden, particularly when the number of uncertain parameters is large or when the model structure is complex. Posterior inference often relies on sampling-based methods such as Markov Chain Monte Carlo, which require generating thousands or millions of samples to approximate the target distribution (Nannapaneni et al., 2020; Onyeka and Emeka, 2025; Shi et al., 2024). Okpala et al. (2024) noted that prediction or inference in Bayesian networks is computationally expensive because it is mostly sampling-based, although analytical estimation is possible in special cases involving discrete or Gaussian variables. As the number of process parameters increases, their estimation using sensor data in real time becomes increasingly costly (Nannapaneni et al., 2020). Nannapaneni et al. (2020) addressed this by applying variance-based global sensitivity analysis for dimension reduction, reducing the parameter space to make real-time analysis feasible for a cyber-physical turning process. Shi et al. (2024) observed that the complexity of manufacturing scenarios is increasing with the integration of intelligent technology, which compounds the computational demands of uncertainty quantification. Lian et al. (2021) proposed a variational Bayesian structural time-series model as an alternative to MCMC, noting that variational inference does not achieve higher computing speed than MCMC in all cases but produces approximate posterior inference results with the advantage of being more scalable to large datasets. Battula et al. (2024) reviewed uncertainty quantification techniques for digital twins in smart manufacturing and robotics, identifying the trade-off between computational cost and fidelity as a persistent challenge across Bayesian methods applied to real-time systems. The computational cost of Bayesian inference remains a practical barrier to adoption, especially in manufacturing environments where decisions must be made within tight time constraints and data arrive continuously.

Model Specification and Prior Selection

Choosing appropriate priors is a critical step in Bayesian analysis, and the choice directly influences the posterior distribution and subsequent decisions. When informative priors are used, they encode existing knowledge about the process, but poorly specified priors introduce bias into the results (Kargar et al., 2013; Chidiebube et al., 2025; Labha et al., 2025). Kargar et al. (2013) used an informative normal prior distribution for the process capability index Cpk, relying on the characteristics of sufficient statistics to derive the posterior. The quality of the resulting capability assessment depends on how well the prior

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reflects actual process behaviour (Kargar et al., 2013). Dong et al. (2023) developed a formal expert elicitation procedure for generating informative priors in material flow analysis. They interviewed eight experts, combined their distributions, and weighted them according to demonstrated expertise in response to seeding questions (Chidiebube et al., 2025b). This structured approach addresses the subjectivity inherent in prior specification, but it is resource-intensive and requires access to domain experts. Labha et al. (2025) noted the use of prior data and expert opinion to extract the prior predictive distribution and elicit hyperparameters for a Bayesian EWMA control chart, emphasizing the practical flexibility this provides in real-world scenarios. When prior information is weak or unavailable, weakly informative or noninformative priors are adopted. Dong et al. (2023) used sensible, weakly informative priors for learning data noise concurrent with parametric uncertainty. The sensitivity of results to prior choice is a recognized concern. Nwamekwe et al. (2025h) demonstrated five scenarios for updating flexural strength uncertainty, showing how different relationships between the prior model and incoming data affect the posterior. When the model underestimates or overestimates the true value, the posterior adjusts accordingly, but the rate and extent of adjustment depend on the prior specification (Okpala et al., 2025a). Schach et al. (2025) introduced a hierarchical Bayesian model for biopharmaceutical process variance, where the hierarchical structure itself acts as a form of regularization, reducing sensitivity to individual prior choices by pooling information across products. The absence of standardized guidelines for prior selection in quality control applications remains a gap that limits reproducibility and comparability across studies.

Interpretability and Adoption

Complex probabilistic models present interpretation challenges for practitioners who are accustomed to deterministic quality metrics and fixed control limits. Bayesian models produce posterior distributions, predictive distributions, and probability statements rather than single numbers, which requires a different mode of reasoning (Chidiebube et al., 2025b; Papananias et al., 2022). Dong et al. (2023) emphasized that Bayesian inference allows transparent communication and systematic updating of model uncertainty, but acknowledged the difficulty of defining proper priors and quantifying data noise as barriers to practical implementation. Nwamekwe and Chikwendu (2025) developed a probabilistic framework for product health monitoring that outputs probability density functions and conformance probabilities, supporting the principle of inspection by exception. While this approach provides richer information than a pass-fail determination, it demands that operators and quality engineers understand and act on probabilistic outputs (Nwamekwe & Chikwendu, 2025). Onyeka et al. (2024) recognized the need for standardized representations of Bayesian network models to aid in their communication and exchange, developing a PMML schema for this purpose. The lack of familiarity with Bayesian concepts among manufacturing personnel is a practical obstacle. Shi et al. (2024) proposed a meta-model architecture and uncertainty quantification framework intended to guide reliable process execution, but noted that the complexity of the modelling approach itself adds a layer of difficulty for end users. Nwamekwe et al. (2025b) observed that simulation-based quality control frameworks, while informative, require careful interpretation of results to support sound decision-making. Training programs and simplified visualization tools are needed to bridge the gap between the statistical sophistication of Bayesian models and the operational requirements of shop-floor decision-making.

Real-Time Implementation Constraints

Achieving real-time performance with Bayesian models requires efficient algorithms and careful management of computational resources. Manufacturing processes generate data continuously, and control decisions often must be made within milliseconds or seconds (Nannapaneni et al., 2020; Battula et al., 2024). Nannapaneni et al. (2020) developed a dynamic Bayesian network approach for online monitoring and control of a cyber-physical turning process, where sensor data continuously update process parameters. They applied

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variance-based global sensitivity analysis for dimension reduction to facilitate real-time analysis, recognizing that estimating all process parameters simultaneously from sensor data is computationally prohibitive (Nannapaneni et al., 2020). Battula et al. (2024) reviewed uncertainty quantification for digital twins in smart manufacturing and robotics, identifying real-time adaptive control as a core requirement. They noted that adaptive control strategies enable digital twin systems to rely on real-time data analytics for optimizing decision-making processes, updating models, and adjusting calibration parameters to respond to changing dynamics (Battula et al., 2024). Papananias et al. (2022) presented a product health monitoring system that updates quality predictions with subsequent on-machine measurements in an online incremental learning fashion, achieving an average accuracy better than 5 micrometres for diameter deviation prediction. Their approach uses Gaussian Process Regression and Bayesian information fusion, which are computationally lighter than full MCMC sampling but still require careful implementation to meet timing constraints (Nwamekwe & Chikwendu, 2025). Emeka et al. (2025a) proposed variational Bayesian inference as an alternative to MCMC for time-series forecasting, noting shorter computing times for approximate forecast precision. The trade-off between inference accuracy and computational speed is a persistent tension in real-time Bayesian quality control, and current solutions tend to be application-specific rather than general-purpose.

Integration with Existing Systems

Legacy quality management systems in manufacturing facilities are built around frequentist tools such as Shewhart control charts, process capability indices, and acceptance sampling plans. Integrating Bayesian approaches into these established workflows presents both technical and organizational challenges (Okpala et al., 2024a; Takada et al., 2023; Nwamekwe et al., 2024a). Onyeka et al. (2024) developed a PMML representation for Bayesian networks specifically to address the need for standardized communication and exchange of BN models across the web and between different software platforms. They demonstrated the conversion of analytical models into the BN PMML representation and back through a Python parser, illustrating the schema for a welding process (Onyeka and Emeka, 2025). This standardization effort responds to the practical reality that Bayesian models must interface with existing data systems, enterprise resource planning software, and quality management databases. Takada et al. (2023) noted that conventional control charts arose in the context of low-mix high-volume production and remain deeply embedded in manufacturing practice. Transitioning to Bayesian control charts requires changes in data infrastructure, software tools, and operator training (Takada et al., 2023). Nwamekwe et al. (2024b) combined lean production methods with Bayesian Belief Networks for energy efficiency analysis in a refrigerator factory, demonstrating that Bayesian approaches supplement rather than replace existing lean tools. They noted that when the amount of data is insufficient for sampling, the Bayesian technique used together with analytical decision-making tools assists decision-makers (Nwamekwe et al., 2024a). The integration challenge extends beyond software compatibility to organizational culture. Quality engineers and production managers must see clear value in adopting probabilistic methods before committing to the transition, and the absence of industry-wide standards for Bayesian quality control slows this process.

Lack of Standardized Frameworks

No unified methodology exists for Bayesian quality control across manufacturing domains. Individual studies develop application-specific models, priors, and inference procedures, making it difficult to compare results or transfer methods between settings (Okpala et al., 2024a; Shi et al., 2024; Schach et al., 2025). Onyeka et al. (2024) made a direct contribution toward standardization by developing a PMML representation for Bayesian networks, available in PMML v4.3 released by the Data Mining Group. Their schema accommodates discrete variables, continuous variables, and their combinations, and they demonstrated its use for a welding process (Onyeka and Emeka, 2025). This effort represents a step toward

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interoperability, but it addresses only the representation layer, not the broader methodological framework. Shi et al. (2024) proposed a meta-model architecture and uncertainty quantification framework for uncertainty modelling in manufacturing, aiming to provide a general tool to guide reliable process execution. Their approach combines domain modelling from software engineering with probability-based uncertainty quantification, but the framework has been demonstrated only on simulated production lines and open-source datasets (Nwamekwe et al., 2024b). Schach et al. (2025) introduced a hierarchical Bayesian model for meta-analysis of process variance in biopharmaceutical manufacturing, noting its potential to leverage historical data across products. The model is specific to biopharmaceutical critical quality attributes and does not generalize directly to other manufacturing sectors (Schach et al., 2025). Dong et al. (2023) developed an expert elicitation procedure for generating Bayesian priors in material flow analysis, but acknowledged the procedure's dependence on the availability and quality of expert knowledge. The fragmentation of methods across studies, each with its own prior specification strategy, inference algorithm, and performance metric, limits the ability of practitioners to adopt Bayesian quality control in a systematic and reproducible manner. Developing standardized protocols for prior elicitation, model validation, and performance benchmarking remains an open research need.



Figure 5: Challenges and Trade-offs in Bayesian Quality Control Implementation

Future Directions and Conclusion

AI-Enhanced Bayesian Models

Future work should connect learning methods to Bayesian models through explicit roles, then establish whether the combined approach improves a quality decision under the conditions in which a plant actually operates. The review describes Bayesian networks for representing dependencies among process variables, Gaussian processes for product-health prediction, and dynamic models that update as sensor readings arrive. These approaches provide a route for joining data-driven pattern recognition with probability-based inference. Researchers should test where machine learning adds value: identifying candidate

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interactions, screening high-dimensional sensor streams, selecting informative observations, or estimating parts of a model that are difficult to specify directly.

That division of labour needs care. A flexible algorithm can detect a repeatable pattern without establishing why the process behaves that way. If a model learns from historical correlations alone, an intervention on machine speed, material lot, or drying conditions can produce a different result from its forecast. Bayesian structure should retain process knowledge and make assumptions visible, while learned components should be evaluated for calibration and stability across products, machines, and operating periods.

Researchers should report posterior predictive performance, uncertainty coverage, false alarms, and the consequences of decision errors, not only point-prediction accuracy. Where a model uses expert knowledge, the elicitation procedure and sensitivity of conclusions to prior choices also need to be stated.

A practical research programme can begin with bounded applications, such as using active learning to decide which batch or sensor condition merits additional inspection, or combining a Gaussian process with a Bayesian network for staged quality prediction. Comparisons should include a conventional control-chart baseline and a simpler Bayesian alternative. That makes it possible to tell whether an AI-enhanced model earns its computational and maintenance cost. Where historical records are uneven and instruments differ across production lines, transfer between sites should be tested rather than assumed. The useful advance will be a model that learns from new evidence without losing traceability, and whose uncertainty changes how a quality team acts.

Integration with Digital Twins

A digital twin can give Bayesian quality control a place to connect a process model with live operating evidence. In the applications reviewed, sensor measurements update estimates of process conditions, while uncertainty-aware models support monitoring, prediction, and adjustment. A twin could extend this arrangement by maintaining a current estimate of machine or product state, forecasting the likely quality consequences of operating choices, and comparing those forecasts with subsequent measurements. A useful twin should represent the variables that affect a defined quality decision, at a level of detail the available data and decision time can support.

The central research task is to validate the connection between the twin and the physical process. Sensor bias, missing readings, calibration drift, and changes in material or tooling can make the digital state diverge from the shop floor. A Bayesian update can express uncertainty about that state, but it cannot repair a misspecified process model by itself. Studies should specify how measurements enter the update, how often calibration is checked, and what evidence triggers model revision. They should also compare predictions against later production observations, including periods when operating conditions change. Without this validation, a plausible simulation is insufficient evidence for changing a process setting.

Digital twins also invite counterfactual simulation, such as estimating the expected quality outcome under a different feed rate or temperature. A causal interpretation requires the model to represent the relevant mechanisms and the intervention to be validated against plant evidence. A forecast under familiar conditions and a forecast after changing a control setting answer different questions. A staged pathway is more defensible: first verify state estimation, then test short-horizon quality forecasts, and only then evaluate recommended adjustments in a controlled operating window. Safety limits and operator authority must remain explicit.

For manufacturing plants with existing quality databases, the twin should exchange information with the current monitoring and maintenance systems rather than create a parallel record. Shared identifiers for batches, machines, sensors, and inspection events are essential. A useful twin will preserve a traceable record of inputs, posterior updates, recommendations, and realised outcomes. That record allows engineers to see when the

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model was informative, when it was wrong, and whether model-supported changes improved conformance without increasing downtime or inspection burden.

Scalable Computational Frameworks

Bayesian quality control becomes difficult to sustain when model complexity, data volume, or update frequency exceeds the time and computing resources available to a plant. The review identifies this tension in sampling-based inference, especially for models with many uncertain parameters and continuous sensor input. Markov chain Monte Carlo can provide detailed posterior characterisation, but its cost can be prohibitive for time-sensitive decisions. Variational inference, sequential updating, Gaussian-process methods, and sensitivity-based dimension reduction offer alternatives, each with limits. Approximate inference can introduce error; a reduced parameter set can omit an important source of variation; and a fast algorithm is of little use if its outputs are poorly calibrated.

Future studies should treat computational performance as part of model validity, not as an engineering detail to report at the end. For each application, they should state the number of parameters and observations, hardware, update interval, inference time, convergence or approximation checks, and memory demand. The same evaluation should examine posterior calibration, predictive coverage, shift-detection delay, and the quality decision produced. This will let readers judge whether a speed gain is acceptable for the process risk involved. A millisecond update has little value if it gives unstable probabilities, while an exact analysis that arrives after the production window has closed cannot guide control.

One promising direction is adaptive computation. The system can use a faster approximation during routine operation, then trigger a more detailed analysis when evidence indicates a process shift, a new product, or an unusually uncertain estimate. Sensitivity analysis can identify parameters that drive the decision and reserve computational effort for them. Hierarchical models can pool information across related products where this is justified, while retaining product-specific effects. Such methods need benchmarks using realistic manufacturing streams, including missing data and sensor interruptions, rather than only simulated examples or clean historical datasets.

Scalability also depends on model exchange and reproducibility. Researchers should provide enough information to reconstruct prior specifications, network structure, update rules, and decision thresholds. Shared benchmarks could compare Bayesian control charts, networks, hierarchical models, and simpler alternatives on common tasks. Algorithm choice must remain specific to factory needs, with documented evidence on where each method is adequate, so production teams can select an approach that fits the required decision speed and risk.

Human-Centric Decision Support

Bayesian quality-control systems report posterior probabilities, predictive distributions, and uncertainty intervals. These outputs carry more information than a single pass or fail label, but they also ask operators and quality engineers to reason differently from familiar fixed control limits. A decision-support system must translate the model output into an operational question: Is the evidence sufficient to continue production, hold the batch, adjust a setting, or inspect selected units? That translation should follow an agreed loss structure. The cost of releasing nonconforming product is not the same as the cost of a short hold, a false alarm, or additional inspection, and the decision threshold should reflect those differences.

Interfaces should show the current estimate, its uncertainty, the evidence that changed it, and the rule used to recommend action. A usable explanation should show which sensor readings, process variables, prior assumptions, or model components contributed when the system flags a shift. Where the evidence is weak or conflicting, the display should make that uncertainty visible instead of hiding it behind a traffic-light colour. This is particularly important when a Bayesian model is used for inspection by exception, because an unclear probability can lead to either unnecessary inspection or missed defects.

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Human-centred design also concerns responsibility. Operators know when a tool has been changed, a material lot behaves unusually, or a sensor is not credible. Their observations should enter a documented review process so that recurring exceptions become part of the evidence available for model review. Overrides of safety-critical recommendations should require a recorded reason. Training should cover the meaning of credible intervals, posterior probabilities, model limits, and the circumstances that require escalation. Short, role-specific instruction is more useful than assuming that every production worker needs a full course in Bayesian statistics.

Research should evaluate these systems with the people who will use them. Measures can include the time needed to interpret a warning, agreement between operators, override frequency, false-alarm burden, and whether the recommended action is followed correctly. Testing should include experienced staff and newer operators, different shifts, and realistic production pressure. Integration with existing quality management systems matters here: staff should see Bayesian information in the workflow they use to document nonconformance and corrective action. Adoption will depend on whether the model helps people make a better call, not simply on whether its probability calculations are technically sound.

E. CONCLUSIONS AND SUGGESTIONS

This review shows that Bayesian quality control has value because it represents uncertainty directly, updates process knowledge as evidence accumulates, and expresses quality performance in terms that can inform action. Its relevance is clearest in settings where data are limited, production is high mix, measurements arrive sequentially, or the cost of a wrong quality decision is material. Bayesian control charts, hierarchical models, process-capability analysis, networks, and reliability models address different parts of this problem. They do not form a single interchangeable solution, and their performance depends on how well the model structure, prior information, data stream, and decision rule match the production task.

The evidence reviewed also sets boundaries on the claims that can be made. Many examples are tied to particular processes, products, or modelling choices. Methods demonstrated in a simulation, a single factory, or one manufacturing sector do not establish transfer to another setting. Computational cost remains a constraint for large or fast systems. Prior selection can influence posterior decisions, while practitioners may find probability distributions harder to act on than fixed limits. Existing information systems and quality routines also create transition costs. Each can determine whether a technically sound model is usable and whether its recommendations improve conformance.

The immediate research priority is disciplined evaluation in operational conditions. Studies should compare Bayesian methods with established quality tools, document prior elicitation and model assumptions, assess calibration and decision consequences, and report computational demands. When a model recommends a change, the evaluation should follow the process after that intervention and check for unintended effects on throughput, downtime, inspection workload, and other critical quality attributes. Shared reporting and benchmarking standards would make findings more comparable without forcing every industry to use the same model.

The field will advance when uncertainty estimates are both statistically defensible and operationally intelligible. In practice, a quality engineer needs to know not only the probability that a process is out of control, but also what evidence supports that estimate and what action is justified at the cost of waiting. Bayesian methods can support that judgement while leaving process knowledge, measurement discipline, and accountable decision-making with the people responsible for the line. Their contribution is to clarify the evidence and its limits,

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so that an intervention is chosen for a reason and checked against what the process actually does.

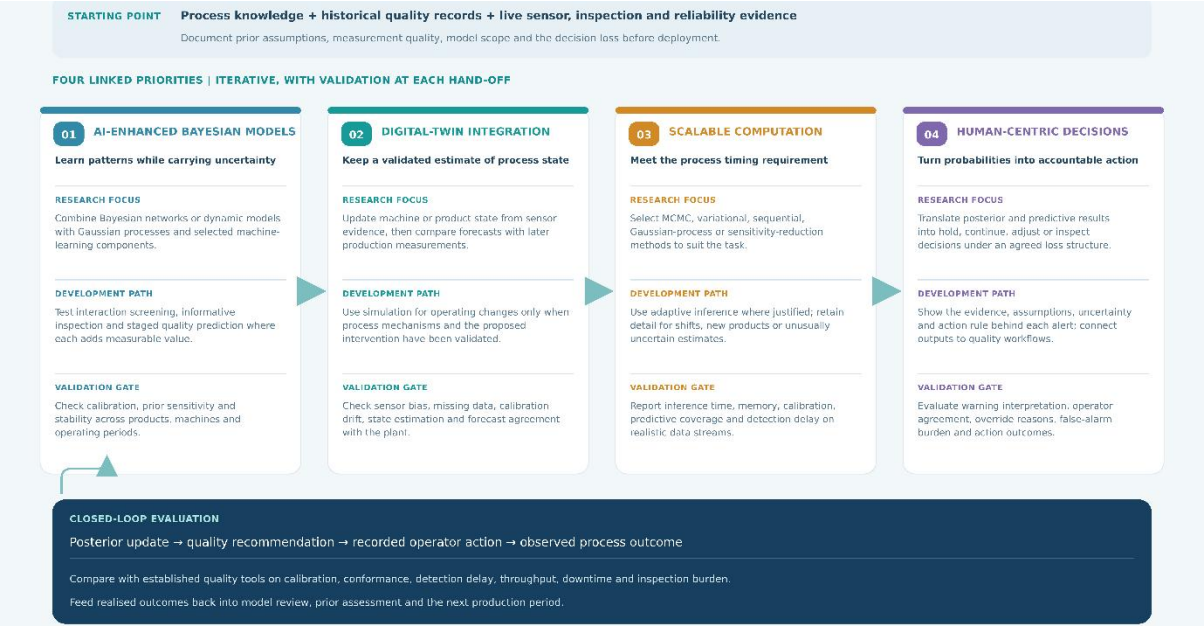


Figure 6: Future Roadmap for Bayesian Quality Control Models in Manufacturing Systems

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