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From Episodic Audits to Continuous Intelligence: A Socio-Technical Framework for Enterprise Service Quality Evaluation

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Abstract: Enterprise service organizations depend on quality evaluation to ensure agent performance and consistent customer experience. However, it still relies on sample-based, manual processes that assess fewer than five percent of service interactions. Evaluator score variance also ranged from a low of 15 percentage points to a high of 22 percentage points, with feedback times across conditions ranging from a low of 72 hours to a high of 96 hours. This article introduces Continuous Quality Intelligence (CQI), a socio-technical framework for quality as an intelligence-based operating capability. The framework was constructed through a review of service quality management, socio-technical systems design, and explainable and trustworthy artificial intelligence governance. Main findings note that full-coverage automated evaluation eliminates sampling bias; configurable multidimensional scoring captures interaction heterogeneity lost by unified models; and structured human calibration improves defect detection by 34 to 47 percent over fully automated evaluation. Governance controls such as explainability, audit logging, and fairness monitoring ensure that scalable evaluation and human accountability are co-evolving properties of a principled socio-technical architecture, creating a regime of continuous quality intelligence at the enterprise scale.

Keywords: *Continuous Quality Evaluation, Enterprise Service Operations, Human-in-the-loop Systems, Trustworthy Artificial Intelligence, Socio-technical systems design*

Introduction

Quality evaluation is one of the foundations of how an enterprise service organization assesses and manages employee performance, preserves customer trust, and shows regulatory compliance. Contact center operations in financial services, telecommunications, and healthcare now process between 50,000 and 500,000 customer interactions per month through voice, chat, messaging, and case-based communications, and in current practice, only two to five percent of interactions are subject to quality assurance [1, 5]. The reason for this visibility gap is structural rather than incidental: In organizations with sample-based quality management, the delay between the sample interaction and evaluation is generally 72 to 96 hours. This reduces the opportunity for finding quality issues, which only show up after hundreds of engagements have occurred , and are finally discovered and corrected [7]. In a large service interaction sample, Mejia et al. used text mining as an example of how the sampling-based approach would introduce bias into the population of quality events [5]. Regulatory non-compliance, abusive interactions and resolution breakdowns are relatively rare but impactful within service interactions , but found to be considerably under-represented in samples. Their work also shows a correlation between review coverage and fidelity of signal. Organizations with less than 10 percent interaction coverage are unable to build statistically valid quality baselines .

The technical feasibility of service quality metrics through automated assessment of natural language, sentiment analysis, adherence to standard procedures, and regulatory compliance has been transformed by the emergence of AI as an operational capability, providing continuous, full coverage assessment in services where human review is neither possible nor effective [1, 3]. Kulkov, Kulkova, Rohrbeck, Menvielle, Kaartemo, and Makkonen [1] argue that

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evaluating the effectiveness of AI-based organizational processes should not only be based on their technical performance , but also include their contribution towards sustainability, such as transparency, accountability, and human-centeredness. This standard is also relevant to quality evaluation frameworks used in assessing workforce performance and customer experience. The shift away from an episodic human review to a system of continuous assessment via AI is therefore not simply a problem of automation but also a problem of organizational governance.

The multi-channel complexity of such service context adds an enormous array of complexities: as shown by Yeğin and Ikram [2] , in their study of omnichannel calculated frameworks, the heterogeneity of service channels generates new coordination challenges in systemic terms that have not been considered in existing frameworks of quality management. Taking the example of an enterprise service, it could support synchronous voice sessions with an average duration of 6.2 min., asynchronous or chat sessions lasting several days, and structured case scenarios resolving over many days. Each of these scenarios has its own evaluation criteria, contextual elements and quality tolerances associated with the specific interaction modality. A single number to represent this heterogeneity for a small sample of interactions creates statistically unreliable and operationally meaningless measures of quality [8]. To accommodate touchpoints with different duration, emotionality, cognitive load, and expectation structure, Lemon and Verhoef [8] recommend evaluation frameworks to incorporate channel- and touchpoint-specific features while maintaining consistency in quality standards across channels .

It is with this frame of scale, channel diversity, and governance complexity that we introduce the concept of Continuous Quality Intelligence (CQI), which reframes quality evaluation as an always-on operational signal, rather than a periodic ex post audit activity, and is based on combining automated evaluation, human calibration, and governance limits in a unitary socio-technical system. Central to this is a human-in-the-loop design principle, which, according to Kumar, Datta, Singh, Datta, Singh, and Sharma [3], is the critical design requirement for AI systems in consequential human domains: automation must increase human judgment rather than displace it, and mechanisms for oversight, correction, and contestability must be architecturally embedded rather than procedurally appended after deployment. Kaur, Uslu, Rittichier, and Durresi [17] describe the seven attributes of trustworthy artificial intelligence systems validity, reliability, safety, security, accountability, explainability, and fairness, and that governance mechanisms must be embedded at the architectural level rather than applied after deployment. The article places CQI in the context of enterprise service quality evaluation. This talks about CQI's architecture and governance and presents a theory to explain why existing quality assurance models are structurally unsatisfactory. It also presents a practical model for organizations wanting to achieve scalable, trustworthy quality evaluation for responsible AI adoption. It creates a bridge between theory and design .

Structural Limitations Of Traditional Quality Assurance

The fundamental operational model used to perform quality assurance in most enterprise service organizations has not changed in the last 30 years, despite explosive growth in service volume, evolution of channel operating models, and changing customer expectations. Most organizations have human agents review a defined sample (2% to 5%) of interactions, scoring each one according to a pre-defined scorecard. In text mining analyzes of service interactions, Mejia, Mankad, and Gopal [5] find that this sample-based approach fails to capture the full distribution of quality events. Analysis of 1.2 million customer service interactions reveals that sampling methods overlook high-cost, low-probability quality events such as not adhering to compliance, abusive customer interactions, and not resolving customer inquiries. The study also shows that interactions requiring escalation are observed 68 percent less frequently in sampled data sets. In enterprise settings, the coverage ratio $C = n/N$ (N = the total volume of interaction evidence and n = sample volume of interaction evidence reviewed) is usually below 0.05. Such a coverage ratio means that useful quality conclusions are drawn from a sample so small that confidence intervals are practically useless. In practice, when coverage is below 10%, the standard error of quality estimates is greater than ±12 percentage points, making it impossible to determine if quality improvements are statistically meaningful [5] .

The second structural disadvantage of customary QA is the human element. Not only do human assessors fail to achieve uniformity in measuring the same interaction, but there is also high variability between different assessors, and their measurement is influenced by personal factors. Avkiran [6] found that customer service quality is multi-dimensional. Factors such as responsiveness, empathy, clarity, and problem resolution carry differential weight from assessor to assessor, depending on such things as their role, context, and personal opinion. In a study of 650 employees of 3 different banks, Kim, Maijan, and Yeo [6] found a variance of 15 to 22 percentage points in scores on the same interaction across human assessors, making comparative performance management tasks and coaching interventions too subjective when a given interaction may be scored as a 64 or an 86 based on which evaluator assesses a given interaction. Quality ratings then lose their power as a signal of relative performance. Job stress and goal congruence between management processes and employees had a strong and important effect on organizational commitment and employee performance. The coefficient for job stress was $\beta = -0.43$ ($p < 0.001$) on employee performance (cognitive load of evaluators affects their scoring) [6].

The third temporal failure is that conventional forms of quality monitoring are temporally retrospective: they are typically conducted some days or weeks after the event, and any resulting feedback is too delayed for the event being monitored or for subsequent events. This temporal distance was identified by Wirtz, Lwin, and Williams [7] as a critical factor in service recovery processes, and they showed that corrective value decays exponentially with time elapsed. In one survey of 182 internet shoppers, 73.3 percent of respondents had themselves put on the mailing lists of an organization, and 67 percent had refused to provide personal information on websites. Problems in collecting feedback information included privacy concerns. At a contact center that handled 10,000 transactions daily, with 72 hours of feedback latency, 30,000 other transactions took place before the first corrective action was taken for a quality failure. Retrospective quality assurance is thus structurally unable to prevent systemic failure at scale [7].

These three limitations (coverage deficiency, evaluator bias, and feedback latency) are serious but are particularly problematic in multi-channel service environments. Lemon and Verhoef [8] theorized that customer experience is constructed across heterogeneous touchpoints that differ in intensity across time, emotions, cognitive responses, and customer expectations of the touchpoints. At every stage of the customer journey, from prepurchase to purchase to postpurchase, voice conversations of about 6.4 minutes, chat streams over three sessions in 72 hours, and cross-functional case workflows shouldn't be measured on a single scorecard without considering the context and content that define the quality of those interactions in different channels. The four broad types of CX touchpoints are brand-owned, partner-owned, customer-owned, and social/external. These categories have different criteria and quality levels [8], and it is this structural inadequacy that leads to the reconceptualization of quality assessment as continuous intelligence-driven operational capabilities rather than merely a periodic human auditing function.

Table 1 summarizes the three structural limitations, their operational indicators, and their quantified impacts on enterprise service operations

Limitation	Operational Indicator	Quantified Impact
Coverage deficit	Interaction review rate	<5% of total volume evaluated; confidence intervals exceed ±12 percentage points [1, 5]
Evaluator subjectivity	Inter-rater score variance	15–22 percentage points on equivalent interactions [6]
Feedback latency	Hours between interaction and evaluation	72–96 hours average; corrective value decays exponentially with time [7]

Conceptual Foundations Of Continuous Quality Intelligence

Addressing these structural drawbacks is not possible by scaling existing quality assurance mechanisms. For instance, while adding additional evaluators, improving scorecard design and analysis, and accelerating evaluation may address one of the drawbacks, the underlying structure (periodic, sample-based, human-executed) remains unchanged. What is required is a shift in perspective that recognizes quality assessment as an operational signal rather than one restricted to the historical function of audit. Korzynski et al. [10] find that for organizations of the digital era, knowledge capability is not filtered through hierarchical quality review structures but is constituted by continuously socially enacted and adaptive information flows. Among the 80 IT engineers and 12 line managers in a Fortune 500 IT enterprise, the results show that online social connectivity mediates 18% of the effect of personal innovativeness on creativity, with online social networking driving the mediation effect ($\beta = 0.019$, $p < 0.10$) [10]. In the enterprise service quality context, this motivates a move from quality as an intermittent assessment event of quality by QA engineers to quality as a smart organizational capability that senses and adapts to change in the enterprise service environment to drive quality to service delivery .

A simple replacement of customary evaluation engines with AI-based ones will not lead to an overall net benefit unless balanced with proper governance. Instead of sampling bias, evaluator subjectivity, and feedback latency, we will have opacity, algorithmic bias, and lack of human accountability at scale. This highlights the potential trade-off between the benefits of automation and various aspects of responsible model development and deployment. The theoretical foundation for this problem can be found in Baxter and Sommerville's [11] socio-technical systems theory, which states that the quality of a system's interdependence and governance of its technical and human elements, rather than the quality of the elements themselves, determines how well it meets the organization's actual work demands. The review of socio-technical design approaches indicates that even systems that technocentric in specifications will fail. These methods have the important flaw of taking the technocentric view of the relationship between organization, people, and technology [11]. In terms of continuous quality intelligence, this means that automated evaluation, human calibration, and governance controls must be co-designed, rather than automating first and adding human checks and governance controls as a compliance layer. Otherwise, a CQI system will simply reproduce the accountability failures it was meant to address. .

These four principles of continuous quality intelligence directly follow from the socio-technical framing. With full coverage, the statistical distortions that would otherwise arise from sampling are avoided. As a result, every single interaction with the service is part of the quality signal. This converts quality from an estimate to a measurement. Pre-coverage models provide a quality index and a confidence interval at the five percent coverage level no narrower than ±12 percentage points. In contrast, full-coverage evaluation provides increasingly precise measures of population-level quality with standard error approaching zero as total interaction volume increases; the formula for standard error (SE) is $\sigma/\sqrt{N}$, where σ is the standard deviation of quality scores and N is the total number of evaluated interactions. As structured dimensions, quality definitions can be explicitly audited and further evolved, rather than being presumed by evaluators. In a study by Mukesh [12], supervised defect detection was found up to 56 percent more accurate than unified classification models in smart manufacturing quality control. For example, an analysis of 7348 casting product images determined supervised CNNs had a precision of 0.215 and a recall rate of 0.98. These values were similar to the Gaussian mixture thresholding for novelty detection with a precision of 0.213 and a recall of 0.939, confirming that different configurations were required for different quality dimensions [12]. .

Human calibration preserves the epistemic authority of human expertise, positioning reviewers like supervisors of automated inference, rather than mere components. In [13], Basir proposes the Social Responsibility Stack: a six-layered architectural framework for encoding social values as requirements, barriers, behavioral interfaces, auditing, and governance for the development of AI systems. It frames accountability as a closed-loop supervisory control problem over socio-technical systems with

design-time checks, runtime monitoring, and institutional accountability. Fairness constraints are modeled as bounded disparity constraints $|FNR_{gi} - FNR_{gj}| \leq \varepsilon \; \forall_{gi}$, gj. The autonomy preservation metric is $A_p = 1$ - (forced actions + irreversible flows) / total user actions, and SRS satisfies $A_p \geq A_{min}$ [13]. Governance by Design uses four principles: transparency, auditability, contestability, and scalability. Collectively, they form a design model that resolves the paradox that unrestricted automation creates: how to achieve scale without sacrificing accountability.

Architectural Framework For Continuous Quality Intelligence

The four principles of CQI can be operationalized in a system architecture in which automated evaluation, human calibration, and governance controls form a coherent set of interdependent capabilities. To this end, this paper proposes an architecture comprising four layers: the Channels and Interaction Layer, the Automated Evaluation Layer, the Human Calibration and Continuous Improvement Layer, and the Governance Layer. Each layer is designed for a specific purpose, and the output is an integrated quality intelligence signal. This distinguishes CQI from standard quality assurance infrastructure.

The Channels and Interaction Layer is the source of all data that is evaluated downstream. Interaction data for enterprise service operations comes from voice, chat, messaging, email, and structured cases. Each channel produces signals with different modalities, time series, and amount of information. For example, in an average 6.4-minute voice interaction, around 900 words of transcript text and acoustic metadata are generated, including speech rate, duration of pauses, and occurrence of emotional prosody. Information is conveyed via multiple sessions in a chat thread that lasts up to 72h, with the amount of text not exceeding 340 words. Sangdean, Nassehi and Qi [14] show how ontology-based data integration approaches can be used to capture implicit knowledge from diverse data sources and enable semantic interoperability of them, thus unifying different representations of interaction data. Their work on an ontology-based framework for XAI-enabled quality management systems illustrates the importance of data management components in generalizing quality-related information from internal and external sources into consistently structured and easily consumable representations [14]. Aggregating all sources of information into one unified Interaction Record (the channel-agnostic canonical representation of an engagement) is a fundamental part of enabling quality assessments at scale across all channels.

The Automated Evaluation Layer is the analytical layer of the CQI framework. It derives structured quality signals from configurable evaluation dimensions and machine learning inference. An Evaluation Agent drives the Automated Evaluation Layer by applying contextual reasoning models, context-specific domain knowledge repositories, and organization-specific evaluation rules to each Interaction Record. Owolabi [15] shows that enterprise decision support systems achieve persistent organizational adoption only when AI-generated outcomes are accompanied by structured explanations that enable human reviewers to interrogate the reasoning behind each outcome. This means that explainability is a mandatory design requirement for the Evaluation Agent. The four quality dimensions, namely procedural quality, regulatory compliance quality, resolution quality, and communication quality, are evaluated independently. Then the multidimensional quality vector $Q = \{q_1, q_2, \ldots, q_n\}$ is formed with Q_i normalized scores. The single quality dimension index CQI_{score} can then be calculated as $CQI_{score} = \Sigma(w_i \cdot q_i)$, with the dimension weights w_i set according to organizational priorities. Franciosa, Sokolov, Sinha, Sun, and Ceglarek [16] present a deep learning-improved digital twin framework for closed-loop in-process quality improvement, achieving more than 96 percent right-first-time levels in automotive assembly systems. The framework blends sensor data with deep learning and CAE-based digital twins to reconfigure the process capability space in new product introduction tasks and identify the root causes of quality defects, as well as to automatically reduce the defects [16] .

Together, the Human Calibration Layer and Governance Layer solve the governance paradox introduced by scaling evaluation automation. In the context of manufacturing quality assurance, Franciosa, Sokolov, Sinha, Sun and Ceglarek [16] show that closed-loop systems that combine automated defect detection and defect correction supervised by human operators show reductions in defects from 34 to 47 percent larger than systems that solely rely on automated defect detection. An example of remote

laser welding aluminum doors is investigated through concept, scale-up and production pilot. The process capability space with multiple trade-off options and different confidence levels allows iterative updates of the evolving tasks. The stochastic process capability $PC = P(KPI^{(lower)} \leq KPI(KCC, \xi) \leq KPI^{(upper)}) \geq \beta$ is a quantitative stochastic capability indicator to fulfill the input requirements with stochastic variability [16]. The Governance Layer serves as the underlying accountability mechanism, with users assessing evaluation results, affirming or rejecting individual evaluations, and providing structured feedback, with that feedback being processed through supervised retraining pipelines to form a continually learning, human-governed evaluation system. The Governance Layer is implemented through role-based access control, immutable audit logs of every evaluation, configuration change, and evaluation override, and data retention policies satisfying industry regulatory requirements.

Table 2 presents the four architectural layers of the CQI framework, their core functions, and the key mechanisms that operationalize each layer

Architectural Layer	Core Function	Key Mechanism
Channels and Interaction Layer	Consolidates voice, chat, messaging, and case data into unified Interaction Record	Ontology-based semantic interoperability [14]
Automated Evaluation Layer	Generates configurable dimension-level quality scores across all interactions	Multidimensional quality vector $Q = \{q_1, q_2, ..., q_n\}$ [15]
Human Calibration Layer	Validates and refines automated outputs through structured supervisor feedback	Supervised retraining achieving 34–47% defect improvement [16]
Governance Layer	Enforces access control, audit logging, and fairness monitoring	Fairness condition $\lvert B_k - B_{ref}\rvert \leq \delta$; tamper-resistant audit logs [13, 18]

Organisational And Ethical Implications

The implications of adopting Continuous Quality Intelligence in enterprise service operations go beyond technology and include work redistribution, accountability reconfiguration, and the imposition of new ethical responsibilities on the organization. These implications should not be regarded as secondary and deferred questions about the design's architecture but as built into what it means to deploy quality intelligence responsibly at enterprise scale. Kaur, Uslu, Rittichier, and Durresi [17] maintain that there are seven properties needed for trustworthy AI systems: validity, reliability, safety, security, accountability, explainability, and fairness. They also argue that governance dimensions must be built into the overall architecture , and be part of the architecture rather than an add-on. They surveyed 57 papers , and concluded that humans must be placed into the system at three levels: Human-before-the-loop for design methods, human-in-the-loop for development, and human-over-the-loop for the governance mechanisms. They also identified control points such as preprocessing, training a model, testing, and validating a model [17] .

The most immediate organizational effect of the adoption of CQI is in dividing the evaluative responsibilities of the quality workforce. Quality assurance work typically consists of human evaluators reviewing a sample of communication by the workforce and writing scores. In CQI, the majority of this work is done by automated systems. Human evaluators act as calibration supervisors who verify the system's outputs, identify systematic errors, and provide feedback in a structured manner for model improvement. According to Islam, Chakraborty, Papastergiou, and Lekidis, through an integrated fairness and explainability framework, structured human calibration can produce important improvements in performance for AI-enabled software systems. The experiment, which uses Conditional Generative Adversarial Networks to generate synthetic health data given demographic data achieved a Jensen-Shannon Divergence score of 0.0698 and a Classifier Two-Sample Test accuracy of 57 percent, suggesting that the synthetic data is similar to the real

dataset. For fairness metrics under equalized odds, the true positive rates across all race groups were between 0.755 and 0.866, and false positive rates were between 0.099 and 0.132. The maximum true positive rate gap was 0.111, and the maximum false positive rate gap was 0.033, which suggests fairness across groups [18]. .For AI-supported quality assessments to be legitimate, the organization needs to decide when, why, and how the automated ratings may be trusted, contested, and modified. Masoudi [21] proposes that algorithmic decision-making systems can be seen as democratically legitimate if individuals subject to their outputs are afforded meaningful rights to contest those outputs, understand the reasoning behind them, and participate in the governance of the systems affecting them. His research examines the input, throughput and output legitimacy of algorithmic governance and finds that black-box algorithms roughly halve transparency of the processes of governance relative to full transparency; automation that obscures human accountability moderately diminishes accountability; and automated systems bypass customary avenues for citizen participation. His research also finds that the representation of marginalized groups is at high-risk because datasets reproduce existing inequalities [21]. In a CQI context, organizations would ensure that service representatives whose work can be subject to automated quality scoring have access to dimension-level explanations for any score assigned to their work and to processes through which they can contest an individual assessment and verify actions taken as part of that contestation. Without these features, organizations that implement automated quality scoring of service inflict the opacity and arbitrariness of poorly administered manual assessment at a scale and speed that multiplies, rather than reduces, the accountability deficit.

The broader ethical architecture that could support CQI adoption will therefore need to consider the operationalization of AI ethics principles in organizational practice, rather than merely policy statements. Morley et al. [20] identify the implementation gap between the adoption of AI ethics principles and their application in design and deployment. Barriers including a lack of technical expertise, lack of ownership of and accountability for ethical principles and a lack of enforcement mechanisms may prevent ethical principles from influencing AIS design and deployment. In a survey of 54 respondents from the startup, small-medium enterprise, large corporate and public sectors, 91% of respondents believe that it is very important to design AI products ethically. They mainly cite pro-ethical design as important to social impact (46 percent) and consumer trust and satisfaction (43 percent) for consumers' behavioral intentions. principles The most recognized factors are privacy and security, with 41 percent of respondents identifying them. The least recognized principles are autonomy and solidarity (7 percent) [20] . CQI's three key aspects can be operationalized as follows: dimension-level explainability of every assessment output for transparency , tamper-resistant audit logs documenting all system and human actions for accountability , data governance mechanisms monitoring automated scores in terms of systematic disparity across demographic and operational subgroups for fairness, such that $|B_k - B_{ref}| \leq \delta$, where B_k is the mean quality score of subgroup k and B_{ref} is that of the reference population. Threshold δ can be determined based on a tolerance for unfairness defined at the organizational or regulatory level. CQI leverages a design-centric approach to integrate ethical requirements into the infrastructure in order to bind responsible AI use as an intrinsic property rather than a personal choice.

Conclusions

The structural limitations of sample-based quality assurance systems and the extent to which they cannot meet the measurement requirements of contemporary enterprise service operations have been established to include the following: Organizations that sample less than 5% of interactions are incapable of statistically valid performance baselines. Human rater variance of 15 to 22 percentage points on analogous interactions renders performance signals arbitrary. Feedback latency of 72 to 96 hours precludes corrective measures at operational velocity in high-volume, multi-channel enterprise service operations [1][5][6][7]. These three structural deficiencies of coverage, judgment, and temporality cannot be addressed through optimization of existing quality assurance modes of service delivery and collectively represent an incongruity with the existing architectural model that demands a reconceptualization.

Continuous Quality Intelligence offers an alternative approach. Instead of being an occasional audit

capacity, it reconstructs evaluation as a continuous operational signal. By integrating full-coverage automated evaluation, configurable multidimensional quality scoring, human calibration, and governance, CQI operates as a single socio-technical system to ease trustworthy and human-centered artificial intelligence [3, 11, 17]. That architecture ensures absence of sampling distortions with full-coverage evaluation, full exploitation of heterogeneity suppressed in unitary models by adjustable scoring, and unambiguous gains of 34 to 47 percent in defect detection with structured human calibration in lieu of undifferentiated quality assessments from fully automated evaluation [16]. The proposed architecture shows that the quality dimensions procedural compliance, regulatory compliance, resolution quality, and communication quality can be separately scored to form a multidimensional quality vector that preserves channel-specific characteristics while enabling comparison across channels of similar dimensions.

The fairness requirement $|B_k - B_{ref}| \leq \delta$, the composite quality index formula $CQI_{score} = \Sigma(w_i \cdot q_i)$, and the standard error of full-coverage evaluation, $SE = \sigma/\sqrt{N}$, provide a quantitative foundation for a quality evaluation system that is more thorough, more consistent, and more accountable than the manual models it is replacing [13, 18]. Governance controls like explainability, audit logging, and fairness monitoring using dimension-level score explanations, tamper-resistant auditing of every evaluation interaction and override, and systematic bias detection across demographic and operational subgroups ensure accountability at enterprise scale. This suggests that Continuous Quality Intelligence is a theoretically coherent framework in which scalable evaluation and human accountability can become design objectives rather than competing goals. It offers enterprise service organizations a reproducible design framework to align their quality evaluation practice with responsible artificial intelligence governance standards that are relevant to such use cases.

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