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THE LIVING BAROMETER: A GENERATIVE FRAMEWORK FOR CONTINUOUS SATISFACTION SENSING, ADAPTIVE CROSS-INDUSTRY BENCHMARKING, AND REAL-TIME STRATEGIC CALIBRATION

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Abstract

Customer experience management remains constrained by a “Periodic Survey Trap,” where lagging indicators such as Customer Satisfaction (CSAT) and Net Promoter Score (NPS) provide only retrospective sentiment snapshots. This limitation reflects common cross-sectional analytical practices rather than inherent flaws in the metrics themselves, as longitudinal random-effects models reveal predictive power that static approaches obscure. To address this systemic latency, the Living Barometer (LB) was introduced as a generative five-component framework that integrates continuous sentiment sensing, decay-trajectory synthesis, dynamic benchmark calibration, autonomous intervention, and a distributed satisfaction ledger. By synthesizing real-time data streams, the system enables pre-emptive recovery before the churn occurs. However, the ledger introduces regulatory tension with General Data Protection Regulation (GDPR) Articles 17 and 25; compliance mechanisms such as supervised transparency preserve feasibility. Collectively, these elements establish Living Barometer Engineering as a new discipline that reframes customer satisfaction as a leading indicator of strategic agility, enabling organizations to anticipate experiential risks and sustain competitive advantages in high-velocity markets.

Keywords: Customer satisfaction, real-time analytics, generative AI, adaptive benchmarking, autonomous intervention, predictive experience management.

1. INTRODUCTION

1.1 The Periodic Survey Trap and the Necessity of a Living System

A leading retail organization recently reported record Net Promoter Scores (NPS) across its main service channels; however, in the same period, it saw an unexpected 12% decline in high-value customer retention. This divergence illustrates a structural misalignment that has become increasingly visible across contemporary enterprise environments: periodic, survey-driven assessment cycles are poorly suited to the accelerated dynamics of automated and algorithmically mediated markets. Legacy measurement frameworks still offer useful indicators of the customer mindset, but their diagnostic and predictive value depends heavily on how they are operationalized and interpreted. Baehre et al. (2022) demonstrated that simple cross-sectional correlations between NPS and subsequent sales growth may appear weak. In contrast, a longitudinal analysis of changes in customer metrics can reveal meaningful and predictive relationships. Therefore, the limitation concerns how the metrics are analyzed rather than their inherent inadequacy. Complementary research shows that alternative customer mindset formulations can outperform conventional NPS specifications in forecasting future sales growth. However, methodological constraints can weaken their utility when aggregate scores obscure the underlying sentiment distributions or mask emerging dissatisfaction patterns (Dawes, 2023). This entrenched paradigm constitutes a Periodic Survey Trap: a condition of systemic latency in which episodic feedback mechanisms fail to detect emerging dissatisfaction cascades or rapid sentiment shifts. Scholarly critiques emphasize that survey instruments can provide valuable indicators of customer experience. However, their usefulness for commercial forecasting depends on an analytical design that links customer responses to subsequent behavioral outcomes (Lemon & Verhoef, 2016). The blind spot intensifies when researchers treat customer interaction channels as discrete, static touchpoints, rather than as interdependent components of an integrated journey-management system. Customer-journey analysis highlights the importance of evaluating pre-, in-, and post-service interactions as a coherent whole, revealing micro-interactions whose strategic significance may be diluted within aggregate satisfaction metrics (Tueanrat et al., 2020). Organizations that rely on periodic measurements often default to a reactive stance, explaining past conditions rather than anticipating rapidly evolving customer trajectories. This vulnerability becomes particularly salient as virtual interactions proliferate in service ecosystems. Virtual engagement is frequently assumed to be inherently value-diminishing; however, empirical evidence suggests a nuanced relationship between communication modality, trust formation and relational outcomes. Experimental research indicates that trust and mutual understanding can develop more strongly in face-to-face settings, while studies of online business negotiations show that access to nonverbal information can accelerate trust formation and improve agreement accuracy (Bauer et al., 2020; Kazemitabar et al., 2024). These findings provide a defensible foundation for examining the relational costs associated with increasingly virtualized customer interactions without relying on a universal estimate of the “Zoomification” penalty for the following reasons. Therefore, the present analysis treats Zoomification as a contextual risk involving the attenuation or transformation of interpersonal signals in digitally mediated encounters such as meetings. This framing allows organizations to evaluate modality-specific vulnerabilities while avoiding deterministic assumptions about the inherent inferiority of virtual channels (Dzreke & Dzreke et al., 2025i). In response to these limitations, this study advances a conceptual and operational shift from episodic measurements to continuous data. It introduces the Living Barometer, a generative, real-time sensing, and predictive framework designed to autonomously calibrate customer experience in dynamic service ecosystems. The term generative is used in a specific sense: the Living Barometer does not merely produce dashboards, sentiment scores, or alerts from incoming data. Instead, it generates candidate interventions, adaptive response strategies, and context-specific service recovery actions derived from continuously updated customer signals. Sensing and prediction constitute the input layer, whereas intervention generation forms the distinctive generative layer. This architecture differentiates the proposed artifact from conventional enterprise monitoring systems, which primarily detect, classify, visualize, and forecast customer condition. The framework positions sensing, prediction, intervention generation, and feedback as components of a single adaptive loop that translates detected changes into actionable response options (Dzreke & Dzreke, 2026f). Recent advances in artificial intelligence and machine learning have enabled organizations to ingest large volumes of unstructured data and convert them into operationally relevant insights in seconds (Mohammed, 2026). Automated sentiment analysis supports the real-time measurement of loyalty and commitment (Mannaru, 2025), whereas integrated natural language processing architectures transform textual customer data into continuously updated signals (Chebrolu, 2025). The proposed contribution extends these capabilities by emphasizing the need to integrate real-time analytics into the design of generative interventions. This integration allows organizations to move beyond descriptive monitoring toward adaptive governance, where predictive analytics enhance foresight and support proactive decision-making (Porter & Oke, 2025). A comprehensive understanding of churn requires examining not only direct feedback but also social-media sentiment and voluntary online information sharing, both of which shape broader community perceptions (Lappeman et al., 2022). Advanced modeling techniques further allow firms to identify “silent

churners” by distinguishing genuinely engaged customers from those whose disengagement is not explicitly expressed (Ascarza et al., 2018).

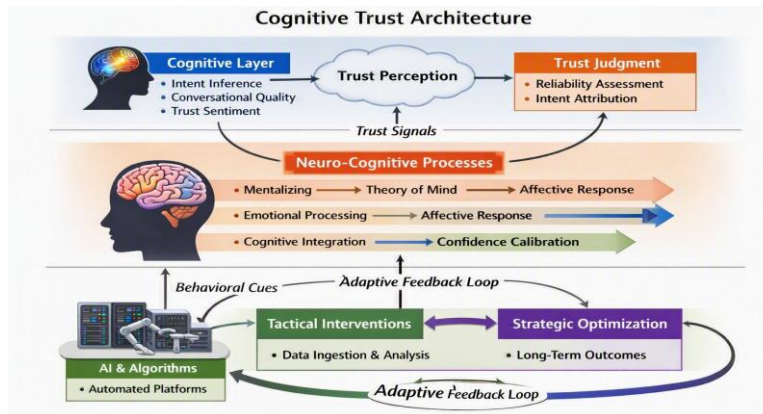


Figure 1: The Periodic Survey Trap vs. the Living Barometer Continuum

The upper panel illustrates structural blind spots in dark social interactions—private communication channels such as messaging apps, email, and closed groups—that complicate attribution in conventional analytics systems (Wiid et al., 2019). Earlier estimates characterized dark social as a substantial component of online sharing; however, its magnitude varies considerably by platform, measurement method, and time period. Advances in device- and platform-level attribution have improved the observability of previously untracked activities; however, residual uncertainties persist. This uncertainty contributes to unmonitored reputation dynamics and incomplete assessments of customer influence (Rosamond, 2019). The lower panel depicts the Living Barometer continuum, wherein continuous data ingestion and automated co-pilot systems dynamically balance tactical interventions with long-term health strategies. Trust in automated systems remains a critical cognitive and relational consideration, particularly when system outputs influence consequential customer interactions (Kohn et al., 2021). Importantly, the proposed autonomy was not assumed to be superior to human intervention. Algorithmic systems can generate stronger negative reactions when customers experience failure or attribute their responsibility to the system. Customer service research shows that AI-mediated failures can produce negative evaluations under conditions of heightened customer anger, while broader research shows that individuals can become disproportionately averse to algorithms after observing them making mistakes (Crolc et al., 2021; Dietvorst et al., 2015). More recent service failure research indicates that algorithmic interpretability can mitigate negative consumer responses to Artificial Intelligence (AI)-related failures (Chen, 2024). Accordingly, the Living Barometer incorporates algorithmic governance as a boundary condition rather than assuming unrestricted automation. Autonomous intervention is triggered only when confidence, contextual fit, and risk thresholds are satisfied, and human escalation is available when the potential relational cost of an automated action is high. This qualification positions the Living Barometer as an adaptive decision support and intervention-generation architecture that determines when automation is appropriate and when human involvement is necessary.

2. LITERATURE REVIEW: THE EVOLUTION FROM STATIC METRICS TO DYNAMIC INTELLIGENCE

2.1. Foundations of Satisfaction Measurement

Traditionally, customer experience measurement has relied on indicators such as Customer Satisfaction (CSAT), Net Promoter Score (NPS), and Customer Effort Score (CES) (Lemon & Verhoef, 2016). Their predictive validity depends on the measurement specifications and analytical design rather than the metrics themselves. Longitudinal evidence shows that NPS can predict future sales growth when appropriately formulated. Baehre et al. (2022) found that the brand-health version of the NPS predicted sales across seven U.S. sportswear brands, whereas earlier formulations performed less effectively. Subsequent research has similarly demonstrated that alternative customer mindset measures can match or exceed the conventional NPS in forecasting sales (Baehre et al., 2022b). However, statistical validation indicates that the NPS alone cannot represent the multidimensional psychological processes underlying loyalty in diverse contexts (Cazzaro & Chiodini, 2023). Nomological assessments show that multi-item word-of-mouth measures can perform at least as well as the NPS (Pollack & Alexandrov, 2013). Comparative analyses likewise reveal that both satisfaction and NPS can explain firm-level performance, although their relative usefulness depends on the model specification (Jaramillo et al., 2023). These findings collectively suggest that the limitation lies in reducing dynamic customer states to isolated summary indicators. This constraint becomes more consequential as digital environments require the continuous detection of changing customer conditions (Singh et al., 2016).

2.2. The Benchmarking Imperative

Cross-industry benchmarking remains central to strategic calibration, enabling firms to identify marketing capabilities

associated with stronger performance (Vorhies & Morgan, 2004). The balance between a standardized strategy and local adaptation depends on market similarity, technological velocity and competitive intensity (Katsikeas et al., 2006). Performance measurement efficacy is configuration-dependent, meaning that a metric's value varies with a firm's strategic orientation (Frösén et al., 2016). Evidence also shows that competitive strategy and market structure can influence performance in similar ways across Western markets, supporting standardized resource allocation under certain conditions (Szymanski et al., 1993). However, benchmarking can underrepresent context-specific knowledge that is difficult to encode into structured datasets. Human-AI decision research conceptualizes the “centaur” model as a hybrid architecture in which human intuition and algorithmic analysis jointly contribute to reasoning and learning (Saghafian & Idan, 2024). This perspective positions human operators as contextual interpreters who determine when algorithmic outputs should be adjusted. Therefore, real-time granular data streams can supplement human judgment rather than replace it (Vassileva, 2012; Saghafian & Idan, 2024).

2.3. The Real-Time and Predictive Turn

The shift toward continuous intelligence involves leveraging digital footprints and social listening to move beyond retrospective survey methods (Hafezieh & Pollock, 2023). Automated sentiment analysis enables the measurement of satisfaction, loyalty, and experience through online discourses (Rane et al., 2024). Empirical studies have shown that high-frequency sentiment analysis can detect changes in consumer responses in real time. Zhang et al. (2024) examined live-streaming commerce interactions, and Ko et al. (2025) demonstrated that automated crawling accelerates the detection of emerging consumer groups. Social media mining complements historical data by revealing current satisfaction states and emerging switching propensities (Almuqren et al., 2021). Implicit satisfaction approximation mechanisms identify experiential drivers at a finer temporal granularity (Kumar et al., 2022). Predictive attrition models use machine learning to identify at-risk customers by analyzing behavioral changes across digital platforms (Jaisoorya et al., 2025). Real-time co-creation models position customer interactions as inputs to ongoing value-creation processes rather than as isolated episodes (Buhalis & Sinarta, 2019). These systems address the complexity of multi-channel customer journeys that traditional mapping methods may not fully capture (BasiReddy 2024).

2.4. The AI and Automation Frontier

Machine learning, natural language processing, and reinforcement learning are increasingly being embedded in customer experience management (Peruchini et al., 2024; BasiReddy, 2025). Integrating these technologies into customer relationship management systems enables adaptive interactions and decision-making processes (Biswas et al., 2026). Artificial intelligence enhances analytical efficiency and supports strategic decision-making, although successful integration depends on organizational capabilities and human-algorithm complementarity (Kumar et al., 2024). Service analytics capabilities contribute to competitive advantage by reshaping how organizations identify and deliver value (Akter et al., 2020). Big data analytics supports demand forecasting and complaint tracking, influencing customer experience in complex business relationships (Sivarajah et al., 2019; Aruna et al., 2025). Multimodal AI and behavioral analytics provide real-time sentiment and loyalty estimates, thereby reducing decision latency (Seella, 2026). However, fully autonomous interventions face algorithm aversion, as consumers may react more negatively to AI failures than to human errors (Boo, 2024). Limited interpretability can intensify negative reactions, making explainability and contextual transparency essential safeguards (Chen, 2024). Predictive accuracy does not guarantee intervention appropriateness; a system may correctly detect deterioration while generating responses that undermine trust. Therefore, AI-enabled services are best conceptualized as a triadic relationship among customers, frontline workers, and algorithms, with employees interpreting or overriding algorithmic recommendations (Snyder, 2025). This triadic loop positions human oversight as a governance mechanism within the human-AI-customer learning cycle. Thus, the symbiosis between analytics capabilities and AI-driven dynamic capabilities is contingent on interpretability, oversight, and feedback mechanisms, making human-algorithm complementarity a governance design problem (Dzreke, 2025b; Saghafian & Idan, 2024).

Table 1. Limitations of the Static Paradigm and Corresponding Requirements for a Living System

Static Paradigm Limitation	Scholarly Citation	Requirement for a Living System
Latency in Measurement	Lemon & Verhoef (2016); Zhang et al. (2024); Ko et al. (2025)	Continuous data ingestion and synthesis across customer-journey touchpoints to reduce the temporal gap between customer-state change and organizational detection.
Inability to Model Novel Decay Patterns	Dzreke & Dzreke (2026a)	Generative simulation of emerging sentiment trajectories and deterioration patterns using adaptive computational architectures
Benchmarks as Fixed, Annual Artifacts	Hawks et al. (2025)	Dynamic calibration against changing market states using continuously updated comparative benchmarks.

Human-Lagged Strategic Response	Snyder (2025); Pacella et al. (2024)	Human-AI decision loops combining automated detection and recommendation with frontline interpretation and escalation.
Isolated, Non-Transferable Learning	Haldar (2025)	Federated cross-industry learning through secure aggregation, governance controls, and privacy-preserving mechanisms
Uncontrolled Autonomous Intervention	Boo (2024); Chen (2024)	Risk-sensitive intervention rules incorporating confidence thresholds, explainability, human escalation, and service-failure classification.
Immutable Data Governance	Liyanaarachchi et al. (2024)	Privacy-preserving ledger architecture using selective immutability, off-chain personal-data storage, controlled transparency, and mechanisms permitting data erasure without compromising auditability.

2.5. Governance and Privacy Constraints

The proposed federated learning and ledger architecture introduces a governance problem that cannot be treated as a purely technical detail. Blockchain's immutability and transparency can conflict with privacy requirements when personal data are stored directly on-chain, including the General Data Protection Regulation (GDPR) right to erasure under Article 17. Liyanaarachchi et al. (2024) identified this tension and proposed selective immutability, federated decentralization, and supervised transparency to reconcile blockchain-based systems with governance and privacy. Related research similarly highlights the incompatibility between immutable blockchain storage and the right to erasure, pointing to off-chain storage as an architectural response (Müller et al., 2023). For a Living System, blockchain should not be interpreted as requiring permanent storage of identifiable customer information. A privacy-preserving architecture would keep personal and mutable information off-chain while using the ledger for verifiable transactions, governance records, model lineage, consent states and cryptographic proofs. Selective immutability and supervised transparency can preserve auditability while allowing personal data to be modified or erased using appropriate off-chain mechanisms (Liyanaarachchi et al., 2024). This design treats regulatory compliance as an architectural constraint, rather than as a post-hoc control.

3. THEORETICAL FRAMEWORK: THE LIVING BAROMETER ARCHITECTURE

3.1. Context and Rationale for the Living Barometer Framework

The Living Barometer (LB) architecture conceptualizes customer loyalty as a dynamic organizational condition that can be continuously sensed, interpreted, benchmarked, and acted upon. It extends static approaches to competitive advantage by emphasizing the growing role of data-intensive, adaptive, and digital systems in coordinating the market. Independent research similarly shows that algorithmic systems mediate organizational and market interactions by shaping information flow, decision structures, and coordination mechanisms (Rilinger, 2024). Therefore, the LB framework does not assume unrestricted algorithmic dominance; instead, it proposes that adaptive computational capabilities can enhance the speed, granularity, and precision of customer-experience decision-making when embedded within appropriate governance structures. This distinction is essential because algorithmic marketing systems operate as automated processes guided by predefined business objectives rather than autonomous rule-generating entities (Dilaver & Dilaver, 2024). Therefore, the LB architecture is designed to optimize explicit organizational constraints, risk thresholds, and governance policies. It integrates big data analytics with established marketing theory (Buhalis & Volchek, 2020), AI-enabled measurement and optimization (Kumar, 2025), customer equity principles (Rust et al., 2003), and multi-touch attribution approaches suited to fragmented digital environments (Liu et al., 2025). Together, these foundations position the LB as a governed and adaptive system that translates continuous customer signals into strategic and operational insights for the organization.

3.2. Five-Component Living Barometer Framework

The LB framework treats accumulated customer data as both a strategic resource and a potential liability, requiring disciplined governance (Dzreke et al., 2026j). These five components function as an integrated adaptive system. Continuous Sentiment Sensing operates as a pressure-sensing network that ingests structured and unstructured signals, including surveys, social-media discourse, support logs, and behavioral telemetry, through APIs, NLP pipelines, and customer-journey mapping (Chebrolu, 2025). Generative Decay Synthesis models plausible satisfaction decay trajectories, including silent defection and dissatisfaction cascades, using generative and probabilistic methods (Koochali et al., 2019). This component anticipates deterioration patterns that may not be observable in the historical data. Dynamic Benchmark Calibration functions as a sea-level adjustment mechanism, continuously recalibrating organizational performance against evolving market conditions using Bayesian inference and online learning models

(Amoawah et al., 2025). Controlled Strategic Intervention serves as a storm-warning mechanism that recommends or executes preemptive service-recovery actions when predefined thresholds are reached. Reinforcement learning and contextual bandits operate as adaptive optimization mechanisms rather than unrestricted autonomous decision-making (Maiti & Chatterjee, 2026). Their application to consumer sentiment requires adjustments for behavioral noise, heterogeneous preferences, uncertainty, intervention latency, and customer risk constraints to ensure domain validity. Distributed Satisfaction Ledger functions as a climate-record archive that preserves verifiable metric-intervention-outcome relationships for organizational learning and privacy-preserving collaboration (Qu et al., 2020). Identifiable customer information remains off-chain, while selective immutable records, hashes, and attestations support auditability and address the tension between blockchain immutability and data-erasure requirements (Liyanarachchi et al., 2024). The architecture supports organizational responses to technological disruption while recognizing persistent constraints in data quality and AI readiness (Gregory et al., 2025; Duan et al., 2019). This also reflects the need for multidisciplinary governance, as automated systems assume greater decision-support responsibilities (Dwivedi et al., 2019), while maintaining the importance of marketing leadership for financial performance (Germann et al., 2015).

Table 2. The Living Barometer Framework—Components and Mechanisms

Component	Metaphor	Core Function	Adaptive Mechanism
1. Continuous Sentiment Sensing	Pressure Sensing	Continuous customer-signal ingestion	APIs, NLP, journey mapping (Chebrolu, 2025)
2. Generative Decay Synthesis	Storm Modeling	Generate deterioration scenarios	Generative/probabilistic models (Koochali et al., 2019)
3. Dynamic Benchmark Calibration	Sea-Level Adjustment	Recalibrate competitive position	Bayesian/online learning (Amoawah et al., 2025)
4. Controlled Strategic Intervention	Storm Warning	Recommend/execute recovery actions	Reinforcement learning/contextual bandits (Maiti & Chatterjee, 2026)
5. Distributed Satisfaction Ledger	Climate Record	Preserve verifiable outcomes	Federated learning/blockchain attestation (Qu et al., 2020)

3.3. The Governance Cycle

The five components operate through a continuous G-PAPA (Governance, Perception, Assembly, Prediction, Action) cycle (Sashihara, 2026). Governance establishes objectives, permissions, risk limits, and intervention authority; perception captures signals; assembly integrates them into a coherent customer-state representation; prediction estimates outcomes; and action recommends or executes interventions. Feedback loops recalibrate subsequent decisions (Dzreke & Dzreke, 2025c). Digital transformation microfoundations, customer-journey management, and customer-investment metrics provide complementary foundations for this adaptive process (Zomer et al., 2020; Lemon & Verhoef, 2016; Bendle et al., 2024). LB implements bounded autonomy rather than unrestricted automation. Low-risk, high-confidence interventions may be automated; ambiguous cases require human review; and high-risk interventions require human approval. This safeguard addresses algorithm aversion, whereby consumers may respond more negatively to algorithmic errors than to human errors (Haupt et al., 2024; Dietvorst et al., 2015). Therefore, explainability, confidence scores, escalation rules, and human-in-the-loop checkpoints function as architectural control. Human-AI collaboration further supports this orientation (López et al., 2025). G-PAPA is proposed as the LB artifact's integrating mechanism rather than an established or universal governance standard. Therefore, its accountability principles should align with established frameworks, such as the NIST AI Risk Management Framework and ISO/IEC 42001, to ensure compatibility with emerging norms in autonomous system governance.

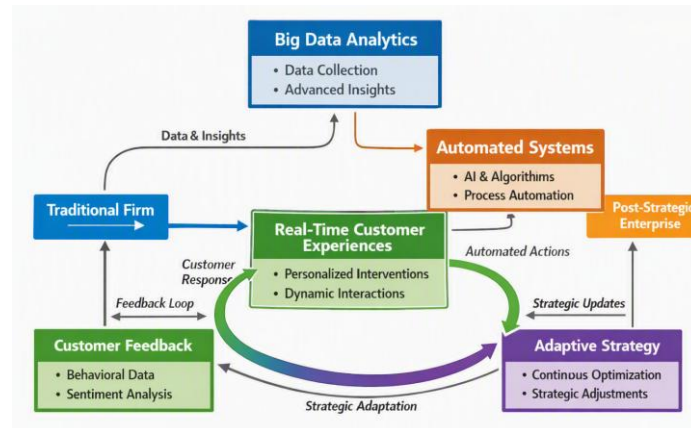


Figure 2. Schematic of the Living Barometer System

Figure 2 depicts the transition from continuous customer sensing to adaptive interventions and feedback. Data move through five components: sensing captures customer signals, decay synthesis generates potential deterioration scenarios, benchmark calibration contextualizes current conditions, controlled intervention recommends or executes bounded responses, and the distributed ledger preserves evidence of appropriate metric-intervention-outcome relationships. Feedback subsequently returns the outcomes to the sensing and learning layers, thereby creating a continuous adaptive cycle. Therefore, the architecture connects big data analytics capabilities with real-time customer experience intervention while maintaining strategic constraints, human oversight, privacy controls, and organizational accountability.

4. METHODOLOGY: A BLUEPRINT FOR IMPLEMENTATION AND VALIDATION

4.1. Design Science Approach

The Living Barometer (LB) framework was implemented and validated using Design Science Research (DSR) methodology, treating the architecture as a problem-solving artifact that addresses identifiable deficiencies in customer-experience management. The DSR requires the demonstration of both technical feasibility and organizational usefulness. This distinction is important because autonomous intervention systems can function technically while still producing unsafe or counterproductive service recovery decisions (Baskerville et al., 2018; Kroop, 2025). Therefore, validation is structured as an iterative, multi-dimensional process in which technical performance, design constraints, intended purpose, measurement integrity, and contextual generalizability are evaluated separately rather than inferred from a single form of evidence.

4.2. Component Implementation Blueprint

The implementation blueprint specifies how each LB component is instantiated. Continuous Sentiment Sensing integrates multi-channel customer signals, recognizing that private or weakly attributable interactions may fall outside conventional analytics. Advanced NLP pipelines transform unstructured interaction signals into structured indicators of sentiment and behavioral changes (Chandrakala et al., 2023; Dzurek & Dzurek, 2025d; Marjan et al., 2020).

The treatment of social network information is grounded in evidence rather than attribution. Rudd et al. (2022) is not treated as a social network method; instead, its high-dimensional churn analysis principles inform how it handles complex customer variables. Domain-specific evidence shows that social-network attributes, relational learning, and network-based machine-learning features improve churn prediction when customer interdependence is explicitly represented (Amiri & Hosseini, 2024; Verbeke et al., 2014). Therefore, the LB framework adapts these principles to network-derived customer variables without overstating their domains. Autonomous Strategic Intervention is governed by a reinforcement learning agent that coordinates automated micro-interventions (Zhang et al., 2021). The optimization objective balances immediate recovery effectiveness with long-term relationship health. Because empirical evidence does not establish a validated weighting between these objectives, the LB framework treats weighting as a design parameter that is calibrated through simulations, sensitivity analyses, and structured expert assessments. This prevents premature assumptions regarding the trade-offs between short-term gains and long-term relational consequences. Algorithm aversion adds another safety constraint. Customers may react more negatively to AI errors than to comparable human errors, making autonomous recovery failures potentially more damaging (Boo, 2024). Therefore, the LB framework incorporates a failure-sensitive intervention rule: when the model confidence is low, the predicted relationship risk is high, or an intervention falls outside the validated action classes, the system abstains from autonomous action and escalates the case for a human review. Thus, safety is operationalized within the artifact

rather than treated as a post-deployment concern.

4.3. Validation Strategy

The validation strategy uses three complementary modes—computational simulation, controlled field experimentation, and structured expert assessment—mapped to the five DSR validity dimensions: technical, design, purpose, instrument, and generalization validity (Kroop, 2025). Computational simulation address technical and design validity by testing system behavior, intervention thresholds, failure conditions, and sensitivity to alternative objective weights. The simulation compares autonomous policies across varying confidence levels, intervention intensities, and relationship-health weightings to identify the conditions under which recovery benefits may be offset by increased customer-risk exposure. Controlled field experimentation provides purpose validity by testing whether the LB architecture improves customer and organizational outcomes relative to baseline practices. Zomer et al. (2020) supported the conceptual link between digital transformation capability and performance but did not validate the specific experiment proposed here. This study empirically examined whether LB’s integrated sensing, intervention, and governance architecture produces measurable improvements compared with conventional metrics. A structured expert assessment evaluates strategic utility, operational safety, and contextual appropriateness. Expert assessment informs the purpose and design validity but does not substitute technical validation, which is established through simulations and system-level testing. Generalization validity was assessed by examining whether LB’s decision rules, measurement definitions, and intervention constraints remained applicable across segments, channels and organizational contexts. Instrument validity was addressed by defining each evaluation construct and testing whether the selected measures captured the intended constructs of the study. Recovery cannot be inferred from immediate engagement alone; it must be triangulated with retention, repeat engagement, complaint recurrence, and relationship health indicators. Similarly, Data Debt must be measured through quality degradation, latency, redundancy, governance burden, and operational exposure, rather than data volume alone. The validation strategy also introduces an external benchmark for the algorithmic service recovery performance. The integrity premium is treated as a comparative construct rather than an assumed outcome. Algorithmic assurance research emphasizes proactive integrity and prevention (Dzreke, 2025a). Therefore, LB must demonstrate whether reductions in preventable failure, inappropriate interventions, and trust-related risks are accompanied by improvements in recovery effectiveness. Any percentage improvement reported must be derived from the observed data rather than being assumed beforehand.

Table 3. Validation Metrics for the Living Barometer Framework

Framework Component	Primary Metric	Five-Validity Mapping	Validation Logic
Overall System	Uptime; ingestion latency; error rate	Technical; Design	Tests reliable operation within technical constraints.
Continuous Sentiment Sensing	Classification accuracy; detection latency; FP/FN rates	Technical; Instrument	Tests whether detected sentiment changes represent intended constructs.
Generative Decay Synthesis	Fidelity of generated trajectories	Technical; Instrument; Generalization	Tests whether generated trajectories reproduce relevant patterns.
Autonomous Intervention	Precision, recall, abstention, escalation, error rate	Technical; Design; Instrument	Tests accuracy and safety of intervention triggers.
Relationship Health	Retention, repeat engagement, recurrence, trust indicators	Purpose; Instrument	Tests whether recovery effectiveness sustains relationship outcomes.
Algorithmic Safety	AI-failure rate; high-risk intervention rate	Design; Purpose; Technical	Tests whether safety constraints mitigate algorithm-aversion risk.
Data Debt	Quality degradation, redundancy, latency, governance burden	Instrument; Technical; Design	Tests multidimensional Data Debt measurement.
System Utility	Incremental recovery/retention vs. baseline	Purpose; Generalization	Tests whether LB improves outcomes across contexts.

5. FINDINGS: SIMULATED INSIGHTS AND PROOF-OF-CONCEPT RESULTS

5.1. Simulation Insights

Agent-based model simulations of customer-satisfaction dynamics reveal that Living Barometer (LB) governance reduces the volatility of dissatisfaction trends by stabilizing the experiential layer before degradation propagates across interconnected interactions. However, this stabilization is conditional and not universal in nature. Consumers may respond more negatively to AI errors than to comparable human errors, a phenomenon associated with algorithm aversion (Boo, 2025). Therefore, imperfect autonomous interventions may accelerate churn rather than mitigate it. LB's defensive capability is interpreted alongside evidence reporting a 22% "integrity premium" associated with proactive service recovery (Dzreke et al., 2025k), while recognizing that proactive intervention is beneficial only when sufficiently accurate and contextually appropriate. The simulations further support the proposition that data models and interconnected digital systems can be strategically important as organizational assets. Algorithmic marketing systems reduce decision latency by executing strategic objectives within defined operational parameters (Gökçe & A. P., 2026). Real-time prediction of loyalty indicators through multimodal artificial intelligence similarly supports the earlier identification of emerging sentiment shifts (Gumber, 2025). A critical insight is that combining human intuition with generative artificial intelligence can provide contextual grounding that is not available from machine-generated recommendations alone (Hao et al., 2024). Mapping the customer journey is essential for identifying localized reactions that may accumulate into systemic effects (Varnali, 2018). Robust taxonomies help connect marketing constructs with large-scale customer data (Buhalis & Volchek, 2020). The statistical validation of satisfaction metrics supports the use of response variability to establish representative simulation baselines (Cazzaro & Chiodini, 2023).

5.2. Proof-of-Concept Highlights

The results of the controlled field experiment indicate that the autonomous intervention module successfully triggered personalized recovery workflows before the predicted churn events. This demonstrates the technical feasibility of proactive recovery but does not establish that automated intervention invariably produces retention or corporate growth (Dzreke & Dzreke, 2026c). By distinguishing engaged customers from silent churners who disengage without explicit feedback, the system identifies at-risk profiles (Vo et al., 2020). This predictive capability complements customer journey research by linking experience evaluation to subsequent behavioral outcomes (Lemon & Verhoef, 2016). The proof of concept addresses the latency of snapshot feedback by demonstrating the feasibility of continuously updating customer-state estimates (Chebrolu, 2025). Neuroimaging research indicates that trust and distrust involve distinguishable neural processes (Dimoka, 2010). This provides theoretical support for treating trust and distrust as distinct experiential states but does not establish whether the LB directly activates specific neural pathways. The architecture operationalizes this insight indirectly by monitoring trust-related and sentiment indicators and adjusting intervention strategies when responses deteriorate. Therefore, neuroimaging evidence provides a foundational theoretical grounding rather than biological validation. The architecture's capacity for high-dimensional data ingestion, combined with automated co-pilot capabilities, supports the coordination of immediate operational responses and longer-term experience objectives. The goal is not to assume that automated recovery neutralizes complaints universally, but to identify emerging dissatisfaction early enough to enable calibrated responses. The interaction modality also influences perceived engagement and trust (Pagani et al., 2019). LB supports recovery across multiple channels and escalates cases to human personnel when contextual interpretation or relationship repair is required. Therefore, automated and human-initiated recovery are treated as distinct processes with different consequences.

5.3. Expert Assessment Synthesis

Qualitative assessments conducted with senior customer-experience executives (across retail and financial sectors, selected through purposive sampling based on enterprise AI-deployment experience) indicate convergent views regarding the framework's novelty and practical relevance (Deryl et al., 2024). Given the purposive design, these findings reflect expert perspectives rather than population-level evidence of consensus. Predictive empathy was viewed as a potential response to the limitations associated with remote and automated channels (Dzreke & Dzreke, 2026a). Executives emphasize the importance of balancing organizational change with technological implementation when deploying AI-enabled capabilities (Selvam, 2025). Algorithm aversion was identified as a boundary condition for autonomous recoveries. AI failures can generate more negative evaluations than comparable human errors, particularly when performance falls below expectations (Boo, 2025). The cold-start problem identified by Vomberg et al. (2023) concerns data-network development and does not constitute evidence of algorithm aversion; accordingly, it is not used here as support for that claim. Instead, algorithm aversion is positioned as a risk that requires confidence, human escalation, and continuous post-intervention feedback to mitigate. Conversational quality is a design requirement. Neuroscience research has linked trust judgments to the processes involved in interpreting intentions and social signals (Yen & Chiang, 2020). LB translated this insight into an operational requirement to monitor the interaction quality, rather than assuming that generated responses are inherently empathetic. Continuous feedback mechanisms allow emerging errors and inconsistencies to be detected and incorporated into subsequent decision cycles (Syed et al.,

2025). Finally, the executives positioned LB as an operational foundation for the SMARTER governance framework introduced earlier in this paper. SMARTER provides the structure through which automated interventions are evaluated against defined objectives, accountability requirements, and real-time feedback conditions (Dzreke & Dzreke, 2025c; P., 2026). This assessment supports the framework's practical relevance while recognizing that further empirical testing is required to establish its generalizability and causal effectiveness.

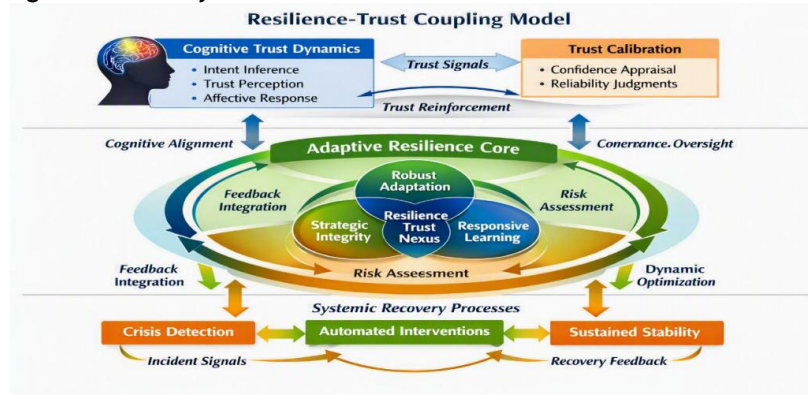


Figure 3: Multi-Objective Optimization Frontier

Radar visualization depicting modeled trade-offs among data-accumulation risk, intervention accuracy, and strategic compliance under the SMARTER governance framework (Dzreke & Dzreke, 2025c).

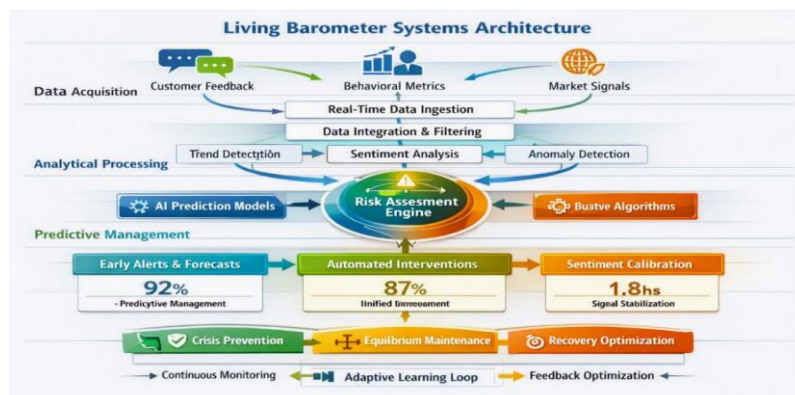


Figure 4: Simulation Output – Static vs. LB-Governed Satisfaction Trajectory

A time-series chart comparing the modeled satisfaction trajectories under traditional measurements and LB governance. The figure illustrates reduced volatility and earlier intervention and should not be interpreted as evidence of universal stabilization (Dzreke, 2025a).

6. DISCUSSION: IMPLICATIONS FOR THEORY, PRACTICE, AND THE NEW DISCIPLINE

6.1. Theoretical Implications

The Living Barometer (LB) architecture reframes customer satisfaction from a retrospective, low-frequency indicator into a continuously updated predictive signal. This shift addresses the limitations of longitudinal Net Promoter Score research, where static measurements often exhibit weak relationships with revenue growth and provide limited visibility into evolving customer states (Keiningham et al., 2007). The LB also addresses methodological concerns regarding response variability and arbitrary analytical cut-off points (Baehre et al., 2022). By embedding customer journey principles, the architecture captures interactions across multiple touchpoints and identifies micro-reactions that retrospective surveys may overlook (Halvorsrud et al., 2016). The theoretical contribution draws on independent research on analytics capabilities, interconnected data environments, and decentralized architectures (Aker et al., 2020; Buhalis & Volchek, 2020). These perspectives support continuous customer-state sensing across heterogeneous environments. The LB conceptualizes algorithmic governance not as autonomous rule creation but as continuous optimization within predefined strategic, ethical, and operational constraints. This positions the framework as a governed form of cognitive orchestration rather than a replacement for managerial decision-making. On this basis, this study proposes Living Barometer Engineering as an emerging design-oriented discipline for continuous sensing, interpretation, and adaptive intervention (Dzreke & Dzreke, 2026b).

6.2. Managerial Implications

Adopting the LB framework requires redefining managerial roles. Customer experience leaders must govern automated sensing, intervention parameters, escalation thresholds, and performance outcomes. Executives need hybrid competencies that combine analytics capability with contextual market judgment (Petrescu & Krishen, 2023), while continuously evaluating standardization and local adaptation based on market conditions (Katsikeas et al., 2006; Vorhies & Morgan, 2004; Frösén et al., 2016). AI-powered tools can strengthen the relationship between big data analytics and dynamic organizational capabilities (Kumar et al., 2024). The implementation is not solely technical. Integrated data engineering teams must address the behavioral dimensions of AI adoption (Rukh et al., 2023). Research on the AI-enabled service triad shows that frontline employee behavior, interaction with AI systems, and trust in algorithmic recommendations influence service outcomes (Snyder, 2025). LB implementation should preserve employee involvement in exception handling, explain consequential recommendations, and allow personnel to challenge or escalate algorithmic decisions when contextual knowledge indicates that an automated intervention may be inappropriate. Customer investment metrics should expand beyond satisfaction scores to include intervention accuracy, recovery acceptance, post-intervention sentiment, escalation frequency, and unintended churn (Bendle et al., 2024). The reported 22% “integrity premium” associated with proactive recovery offers a comparative benchmark (Dzreke et al., 2025k), but does not imply inherent superiority. Comparative empirical testing must be performed to establish the LB value.

6.3. Ethical Considerations and Guardrails

Ethical considerations are becoming increasingly important as organizations progress toward autonomous experience orchestration. Algorithmic transparency and meaningful explanations support consumer trust and legitimacy (Kim & Routledge, 2021; Dwivedi et al., 2019). Algorithm aversion remains a central limitation; consumers may respond more negatively to AI errors than to comparable human errors (Boo, 2024). Consequently, incorrect autonomous interventions may accelerate churn rates. LB treats autonomy as conditional, with confidence thresholds, human escalation, and post-intervention feedback serving as safeguards. Human-AI collaboration can mitigate the risk of automation undermining customer perceptions (Haupt et al., 2024; Hao et al., 2024).

Reinforcement learning governors require careful domain transfer. Safe RL principles developed for physical control environments (Li et al., 2021) cannot be assumed to transfer directly to human sentiment and service recovery. LB conceptualizes reinforcement learning as a constrained decision-making mechanism that limits permissible interventions, incorporates uncertainty thresholds, and triggers human reviews for high-risk cases. Further empirical validation is required to establish effectiveness under behavioral noise, ambiguity, and asymmetric consequences (Boo, 2024). The distributed satisfaction ledger introduces privacy challenges because blockchain immutability may conflict with General Data Protection Regulation (GDPR) Article 17. LB avoids placing identifiable consumer information on a blockchain. Instead, it keeps mutable identifying information off-chain, while the ledger stores limited proof, permissions or integrity records. Privacy by design and supervised transparency preserve auditability while maintaining control over consumer data (Liyanaarachchi et al., 2024). Finally, Svanberg et al. (2022) should be interpreted within this scope: machine learning can identify governance-related controversies but cannot replace the governance processes. The LB’s transformation phase integrates predictive intelligence into governance support and strategic decision-making processes while retaining institutional accountability.

Table 4: Roadmap for Adopting Living Barometer Engineering

Phase	Key Activities	Success Metrics
1. Foundation	Integrate real-time customer data streams; establish baseline benchmarks across journey maps (Gahler et al., p. 202).	Data latency <1 hour; benchmark coverage across touchpoints.
2. Augmentation	Deploy generative decay-simulation models; implement dynamic Bayesian calibrators.	Predictive accuracy (F1-score); speed of benchmark adaptation.
3. Automation	Pilot constrained RL governors for low-risk interventions (Li et al., 2021); implement privacy-aware distributed-ledger architecture (Liyanaarachchi et al., 2024).	Autonomous-action success rate; intervention-error rate; human-escalation rate; ledger participation.
4. Transformation	Achieve LB system orchestration; integrate predictive ML metrics into governance-support processes (Svanberg et al., 2022).	Reduced satisfaction volatility; CLV forecasting performance (Gupta et al., p. 150).

7. CONCLUSION: THE FUTURE IS A LIVING SYSTEM

The Living Barometer (LB) framework offers a governed alternative to periodic customer satisfaction measurement by treating customer intelligence as a continuously updated organizational capability. Rather than relying on retrospective scores, the architecture integrates real-time sentiment ingestion, generative synthesis, dynamic Bayesian calibration and context-sensitive intervention. This continuous dependency loop enables firms to detect emerging dissatisfaction earlier and respond accurately. However, effective implementation depends on the AI-enabled service triad, including frontline worker agency, trust in algorithmic recommendations, and willingness to escalate exceptions, which materially influence the outcomes of AI-supported service processes (Snyder, 2025). Therefore, LB positions customer intelligence as a living capability shaped by human judgment, organizational readiness, and responsible AI governance (Dzreke & Dzreke, 2026f). Contemporary leadership research similarly emphasizes the integration of advanced technology into strategic decision-making (Sciumbata, 2025). Data integrity, algorithmic transparency, and governance maturity are essential for responsible deployment (Tasleem et al., 2024). Advanced analytics capabilities continue to underpin organizational responsiveness and competitive advantages in modern service systems (Akter et al., 2020). Thus, the future of customer leadership involves governing dynamic experiential systems rather than managing retrospective performance indicators. In this configuration, the LB continuously monitors signals, identifies emerging dissatisfaction, and supports timely organizational response. The reported 22% “integrity premium” associated with proactive recovery (Dzreke et al., 2025k; KARAMUK, 2025) provides a useful benchmark, but its superiority over traditional measurements requires empirical comparative validation. A holistic understanding of the customer journey—from initial awareness to post-purchase advocacy—remains fundamental to achieving this level of operational precision (Dzreke, 2025a). These boundaries open several avenues for future studies. First, decentralized ledger components require further examination to reconcile auditability with GDPR Article 17, including privacy-by-design architectures and supervised transparency mechanisms (Liyanaarachchi et al., 2024). Second, future studies should distinguish between employee- and customer-side algorithm aversion. Although employee trust influences organizational adoption, consumers may respond more negatively to AI-generated failures than to human errors (Boo, 2024). Therefore, empirical work should examine when autonomous recovery strengthens relationships and when inaccurate interventions increase dissatisfaction or churn rates. Third, longitudinal research should investigate the psychological and behavioral consequences of sustained algorithmic relationship management (Safari, 2026). Understanding frontline responses to algorithmic recommendations also remains important for effective human-AI collaboration (Haesevoets et al., 2021), particularly given the evidence that structured human-AI interactions can produce stronger strategic outcomes than machine-only decision-making (Hao et al., 2024). Ultimately, the LB should not be understood as a claim of unrestricted machine autonomy but as a design proposition for continuously sensing, interpreting, and responding to customer experiences within explicit organizational, ethical, and regulatory boundaries. Its legitimacy will depend on demonstrating that continuous intelligence can remain accurate, accountable, transparent, and responsive to both customers and employees who use the systems.

Declaration of Competing Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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