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Modeling Customer Journey Friction in Modern Retail Operations: A Data-Driven Framework for Operational Experience Diagnostics

Sushen Sarkar

Abstract: That said, as customer experience is becoming the main competitive battleground in retail, the systems many organizations are relying on to measure it are not, structurally, aligned with the operations that create it, and sentiment-oriented indexes may reflect how customers feel when their interaction ends. They do not explain the process conditions that produced that feeling. An incomplete measurement creates an incomplete body of evidence that improvement teams must work from to design solutions, especially when symptoms may not represent the underlying structures. This article introduces the Customer Journey Friction Modeling (CJFM) framework, a data-driven framework that considers operational process signals as central diagnosis evidence for customer experience management. CJFM is based on four measurable indicators of service friction: interaction volume, transfer frequency, resolution latency, and cross-channel switching behavior. The framework consists of a four-layer architecture comprising data integration, journey reconstruction, analytical method selection, and real-time intervention design. It also discusses the organizational requirements for implementation, including cross-functional governance setup and data quality infrastructure, the role of AI in extending friction detection from retrospective diagnosis to predictive and adaptive service control, and human-AI collaboration in service ecosystems. These points should be given due consideration when implementing large-scale AI in customer-facing service contexts, especially in terms of potential performance improvements and implications for the workforce. Beyond technical investment, closing the gap between sentiment capture and diagnosis requires a structural reorientation in defining, collecting, and deploying customer experience evidence across the service organization.

Keywords: *Customer Journey Friction, Operational Analytics, Service Process Design, CX Diagnostics, Process Mining, Retail Operations*

1. Introduction

Retail service operations generate vast quantities of process data with every customer interaction: call routing records, chat session logs, order management events, and case resolution timestamps. Despite this abundance of operational signal, most customer experience programs anchor their diagnostic work to sentiment surveys collected after the fact. The consequence is a persistent measurement gap. Leaders can observe that satisfaction is declining, but the process record that explains why remains largely unanalyzed. This misalignment between measurement and operational root cause is not a minor inefficiency. It forces improvement teams to rely on intuition or anecdotal escalations when designing remediation efforts, producing interventions that address symptoms rather than structure [1]. Customer Journey Friction Modeling addresses this gap directly. By treating operational data as primary diagnostic evidence, it enables organizations to locate, characterize, and systematically reduce the process friction that shapes customer experience before sentiment surveys are ever deployed [2]. This article presents the framework in full, from its conceptual foundations through to implementation architecture and future capability development.

University of Chicago - Booth School of Business, Chicago, IL, USA

ORCID: 0009-0009-9787-185X

2. The Measurement Gap in Customer Experience Management

2.1 Sentiment Metrics and Their Structural Limitations

Net Promoter Score, Customer Satisfaction Score, and Customer Effort Score have become near-universal fixtures in retail service measurement. Their appeal is clear: they are compact, quantifiable, and directly reflect customer perception. Each metric has genuine utility as a monitoring signal. Customer experience spans the full arc of a customer's relationship with a firm, encompassing cognitive, emotional, behavioral, sensorial, and social responses across all touchpoints [1]. This breadth makes it difficult to compress into a single retrospective score, yet that is precisely what conventional sentiment metrics attempt to do.

Their structural limitation is equally well-documented. All three are retrospective. They capture a customer's evaluated sentiment after the interaction has concluded. They do not record what the customer actually experienced during the service process, how many transfers were required, how long the resolution took, or whether the customer had to contact support multiple times for the same issue [2]. Two customers reporting identical satisfaction scores may have arrived at that score through entirely different service journeys. One may have been resolved in a single interaction, while the other was routed through multiple departments over several days. The causal pathway between process failure and customer dissatisfaction remains opaque when measurement relies on survey outputs alone [9].

Research on customer experience has identified a further structural concern. Experience is not a single-point event but a dynamic process that evolves across pre-purchase, purchase, and post-purchase stages [1]. Sentiment surveys administered at a fixed post-interaction moment cannot capture this temporal dimension. Friction that accumulated during the service interaction may be partially offset by resolution satisfaction, producing a sentiment score that underrepresents the operational disruption the customer experienced. However, condensing a complex journey into a single score can lead to less diagnostic information for improvement teams [9].

2.2 Aggregation Effects and Hidden Variation

The standard practice of reporting customer experience metrics as organizational averages further reduces diagnostic precision. An aggregate score communicates nothing about the distribution of experiences that produced it. High-friction customer segments, where repeat contacts, transfer loops, and extended resolution times are concentrated, may constitute a minority of total volume but account for a disproportionate share of satisfaction losses [4].

A particularly significant dimension of this aggregation problem concerns complaint behavior. Research shows that only 20.1% of frequently purchased products and 20.9% of services generate formal consumer complaints [18]. This means that the vast majority of friction-generating service failures never surface through formal feedback channels at all. Customers, particularly those of lower socioeconomic status, may not be aware of their rights to complain or may choose disengagement over escalation [18]. The complaint data that does reach management therefore represents only a small part of a much larger iceberg of unrecorded service friction. Aggregated sentiment metrics built on survey response files suffer from the same representational gap.

Process variation also maps poorly to survey response rates. Customers with highly negative experiences may disengage before they complete post-interaction surveys, while those with neutral experiences may overrepresent themselves in survey samples. The resulting measurement bias can systematically understate the scale of operational friction in high-complexity service segments [2]. Operational data sidesteps this limitation. Every interaction that enters the service system generates a record, regardless of whether the customer completes a satisfaction survey. This universality of coverage is one of the primary advantages of building friction models on process signals rather than survey response files [3].

2.3 The Case for Operational Diagnostics

Operational diagnostics reframes customer experience analysis as a process problem. It asks customers not how they felt about the service experience but what happened and why. This has ramifications both strategically and analytically. By diagnosing friction at the process level, organizations can tackle root causes of friction. For example, routing logic can be adapted, gaps in the knowledge base can be identified, or escalation thresholds can be adjusted [6].

Operational diagnostics also enables proactive intervention. Sentiment surveys, by definition, cannot surface friction until after it has occurred. Operational signals including elevated handle times, transfer chains, or unusual repeat contact clustering can appear during an active service interaction [13]. A real-time friction detection capability transforms the measurement function from a retrospective audit into a live operational control, which is a structural shift in the role that data plays in service management [3].

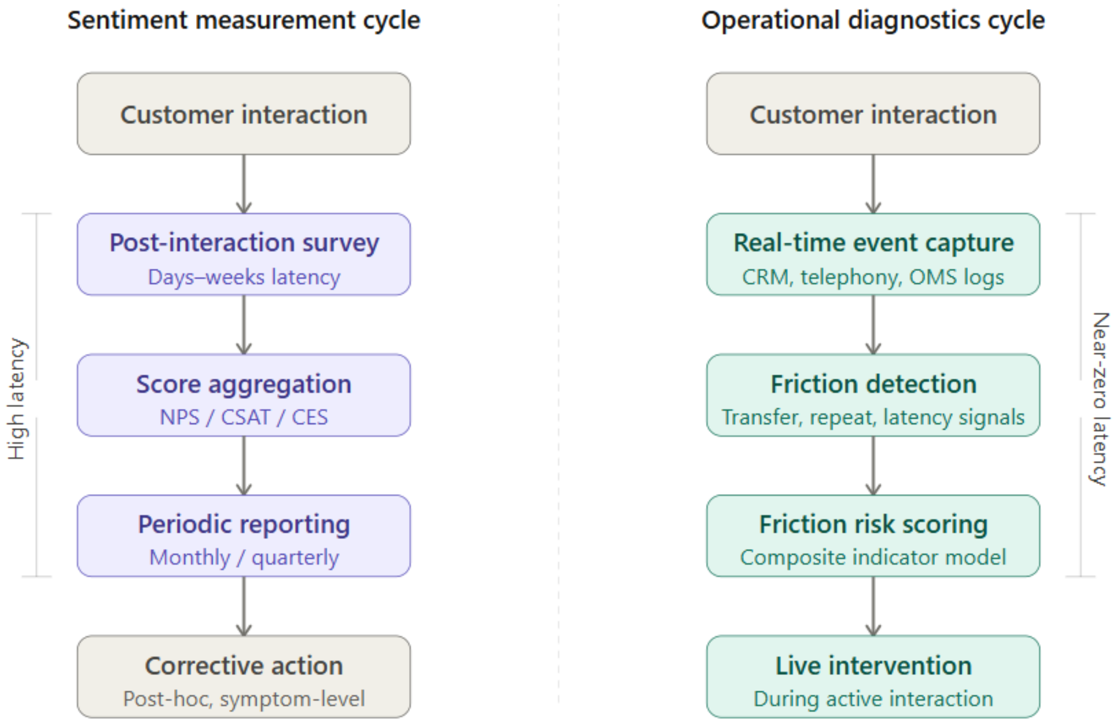

Figure 1: Side-by-Side Comparison Diagram Comparing Sentiment Measurement Cycle and Operational Diagnostics Cycle [1, 6]

3. Customer Journey Friction: Conceptual Framework and Indicator Architecture

3.1 Defining Friction in a Service Context

A process condition that increases the effort, time, or complexity required for the customer to resolve a situation. Friction is a structural property of the service process, not a perceptual state. A customer may not explicitly articulate that a transfer was inefficient or that a second contact was avoidable, but the operational record of those events captures friction regardless of whether the customer's survey response reflects it [9]. The consumer decision journey is not linear. It involves a series of touchpoints at which the potential for friction to accumulate is present at each stage [8]. Treating friction as a structural process property, rather than a perceived outcome, makes it measurable and actionable in a way that sentiment is not.

Friction manifests across several operational dimensions. Temporal friction arises from excessive resolution time, including wait times, handling durations, and multi-day resolution cycles [13]. Research in factory physics and queueing theory establishes that variability in service demand and service capacity are the primary drivers of waiting time and work-in-process accumulation in service systems [12]. These same principles apply directly to contact center and omnichannel service environments: when demand variability exceeds capacity buffers, resolution time distributions develop long right tails that represent the highest-friction customer experiences [13]. Structural friction arises from inefficient routing, handoffs, and silos that split the service process into partitions across workers. Informational friction arises from differences across channels or agents where customers have to repeat contextual information. Recurrence friction occurs when the first contact does not resolve the problem, and future contacts arise [2].

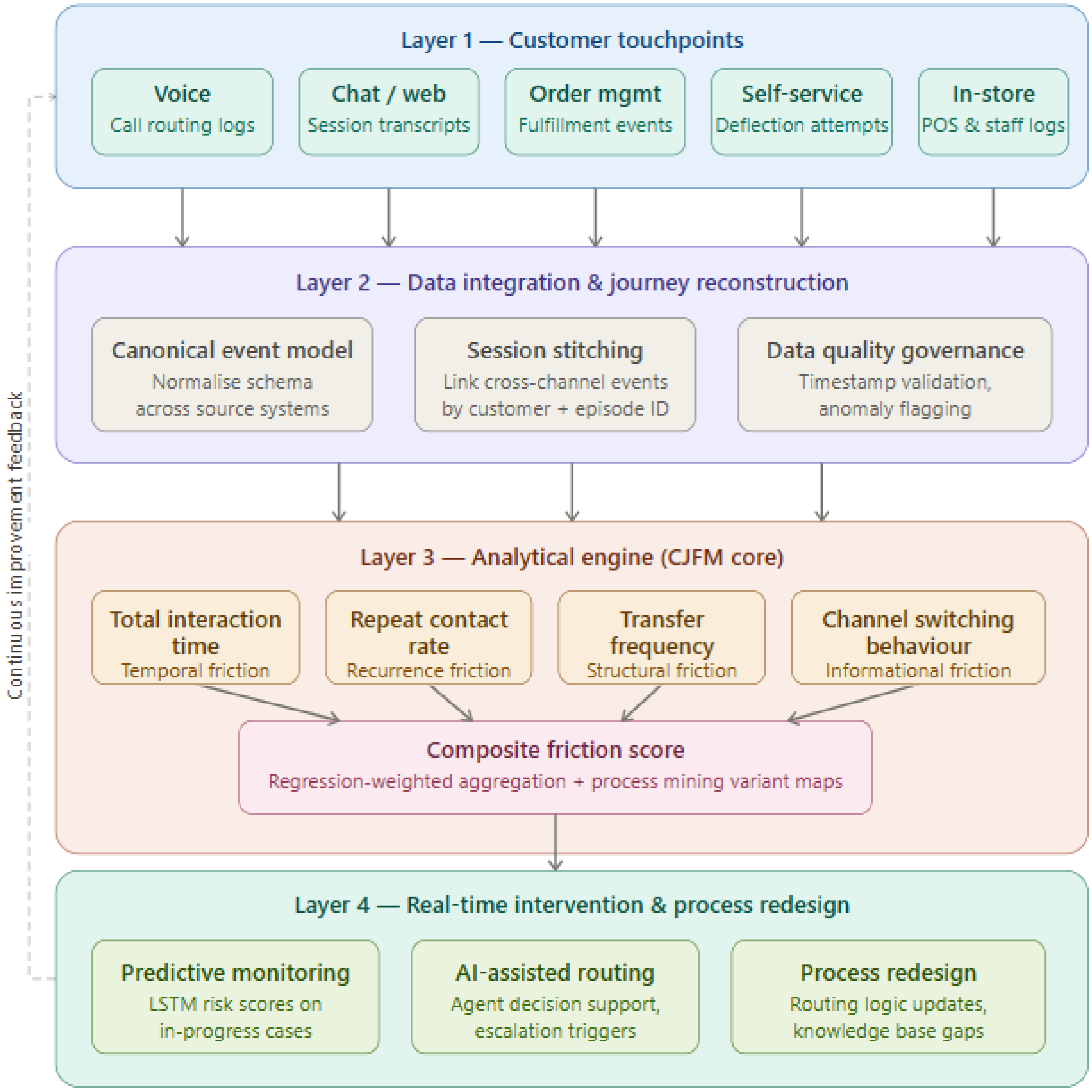

Figure 2: Integration of Customer Journey Friction Modeling (CJFM) across retail operational layers [Author's Synthesis Based on 6, 11, 13]

3.2 Primary Operational Indicators

To develop a friction model, one needs to identify observable friction indicators that can be derived from existing enterprise information sources, that are stable enough over time to be measured, and that are precise enough to differentiate friction levels.

The core indicator set used in Customer Journey Friction Modeling is shown in Table 1 together with its associated friction signal and its main information source for calculating it [6, 13].

Operational Indicator	Definition	Friction Signal	Measurement Approach
Total Interaction Time	Cumulative time across all touchpoints to resolve one issue	High	CRM event logs, timestamp delta
Repeat Contact Rate	Frequency of re-engagement for the same unresolved issue	High	Case linkage logic in support system
Transfer Frequency	Number of agent or department transfers per contact	Medium to High	Call routing logs, chat transcripts
Channel Switching	Movement between service channels before resolution	Medium	Cross-channel session stitching
Resolution Complexity Index	Weighted count of systems, teams, or steps involved	Variable	Workflow metadata, case notes

Table 1: Primary Operational Friction Indicators, Signal Type, and Measurement Sources [6, 13]

Total interaction time is the total time a customer spends with the service system at all touchpoints for a given issue. Extended total interaction time is reliably associated with higher customer effort and lower satisfaction [1]. Research in queueing and service operations establishes that cycle time, the total elapsed time from customer initiation to resolution, is a function of both process work content and variability-induced waiting [12]. Improving cycle time, therefore, requires reducing both the amount of work done in each step and reducing the variability that causes queuing delays between steps [13].

The Repeat Contact Rate (RCR) is the percentage of customers who recontract for the same issue within a specified timeframe. A high repeat contact rate indicates a problem with the initial resolution or that the root cause was not resolved. Case linkage logic (contacts grouped by customer identifier and issue category) [7] is the main information source in CRM systems. Transfer Frequency (TF) computes the number of times in a service episode a customer is transferred between agents, departments, or channels. Each transfer also increases latency and context switching, and, in a study of telephone call centers, the transfer rate was one of the most solid predictors of long handle times and low customer satisfaction [13].

Channel Switching is the number of service channels that a customer uses to reach their resolution or desired outcome. For example, if a customer contacts a business via chat, escalates to voice and then emails, this is considered a three-channel episode [1]. Cross-channel switching both reflects and amplifies friction, as each transition typically requires partial or full context reconstruction [8].

3.3 Composite Friction Scoring

Individual indicators provide useful diagnostic signals in isolation. A composite friction score, constructed by weighting and aggregating indicator values, enables journey-level and segment-level comparison. Weight assignment should reflect the relative contribution of each indicator to satisfaction outcomes, estimated through regression analysis on historical data where survey scores and operational records can be joined [5]. This approach to variable weighting is consistent with the established practice in marketing analytics of using regression-based attribution to quantify the marginal contribution of individual service process variables to overall satisfaction [5].

The composite score serves several analytical purposes. This assists with triage and prioritization based on the ranking of friction intensity, temporal trend analysis, and undertaking a process improvement to see whether the friction has been reduced. It also supports segmentation, where journey clusters with similar friction profiles can be analyzed for shared structural causes [4].

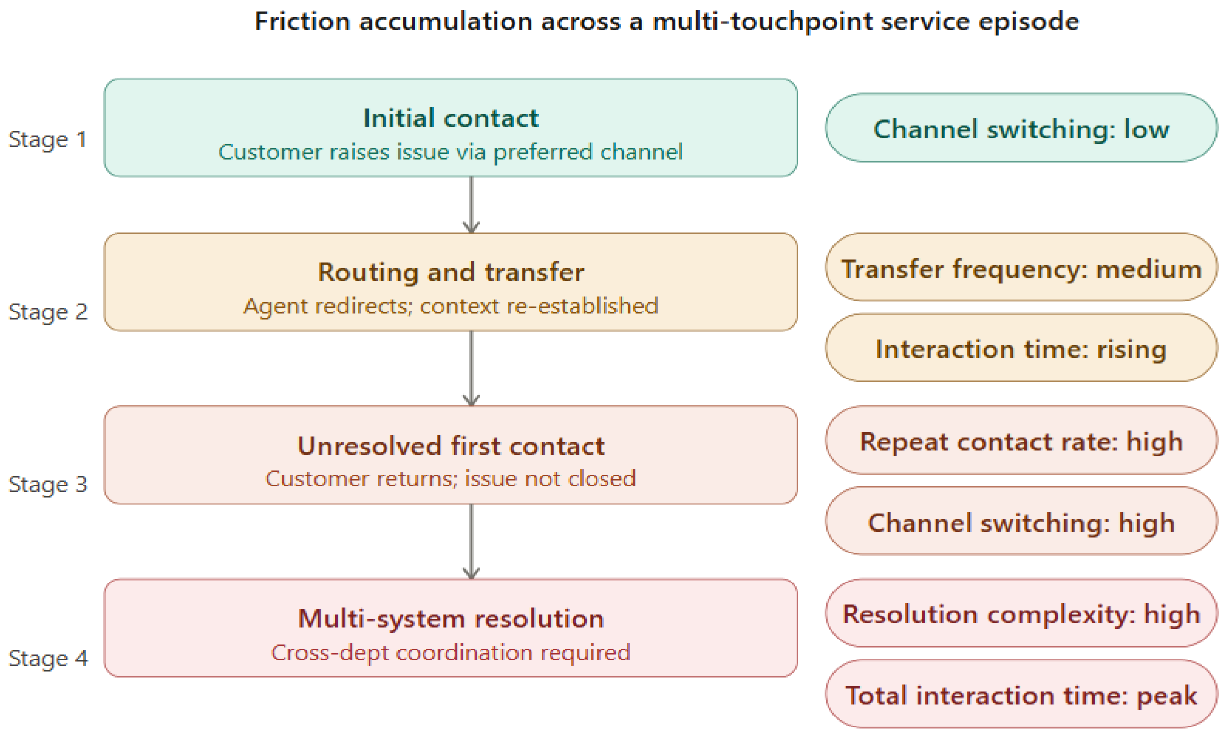

Figure 3: Layered Funnel Illustrating Friction Across Multi-Touchpoint Service Episodes [1, 8]

4. Data Architecture for Friction Modeling

4.1 The Multi-System Data Environment

Customer journeys do not reside in a single system. They are distributed across a range of enterprise platforms, each of which captures a partial view of the interaction [7]. Customer Relationship Management systems hold contact history, case notes, and resolution status. Telephony and workforce management systems capture call duration, queue times, and routing steps. Order Management Systems capture fulfillment events and exceptions. Digital engagement systems capture session metrics, chat transcripts, and self-service attempts. Research on CRM architecture confirms that the analytical value of customer data increases substantially when interaction records from multiple channels are linked into a unified customer view [7].

Friction modeling requires data from most or all of these sources, joined at the customer and episode level. Without integration, each system provides only a fragment of the journey. A contact center record showing a high transfer count is only interpretable in the context of the order management event that triggered the customer contact. The integration layer is therefore not a preprocessing convenience but a structural prerequisite for the entire analytical framework [6]. Process mining research has established that complete event logs, capturing all activities, resources, and timestamps associated with a case, are the foundational data requirement for reconstructing actual process behavior from operational records [6].

4.2 Unified Data Architecture Design

A viable architecture for friction modeling centers on a canonical event model that normalizes interactions from heterogeneous source systems into a consistent schema. Each event record should carry at minimum a customer identifier, an interaction timestamp, an event type classification, a session or episode identifier, and a source system tag [6]. The episode identifier is particularly critical. It links events from different channels and timestamps into a coherent journey record, making it possible to compute total interaction time, transfer count, and channel switch frequency at the episode level [7].

The canonical model can be implemented through several architectural patterns. In a central data warehouse approach, source data is ingested and transformed in batch cycles. It provides a single source of truth for analytical queries, but it can add latency. A streaming architecture based on event buses is more appropriate for live friction detection use cases, as it allows near real-time event consumption and processing. A hybrid of streaming event capture for operational alerting and batch storage for long-term historical analysis can also be a good solution depending on existing infrastructure and whether real-time or retrospective analysis is of higher priority [3].

Data quality governance is a non-negotiable requirement at this layer. The Process Mining Manifesto, which documents foundational standards for event-log-based process analysis, identifies data quality as the primary constraint on the reliability of process mining outputs [10]. Timestamp inconsistencies across systems, missing customer identifiers, and incomplete event sequences each degrade the analytical reliability of friction models. Automated validation rules, anomaly detection on event frequency, and clear data stewardship ownership across source systems are the primary quality control mechanisms [10].

4.3 Journey Reconstruction Logic

A set of session stitching and episode delimitation rules needs to be defined to reconstruct the complete customer journey from the raw event log. Session stitching links all events of a customer if these events happened in the same customer interaction window (usually defined by the maximum inter-event gap). Episode delimitation groups sessions with related issues via a customer identifier, an issue category, and the temporal proximity [6].

Special consideration is needed for edge cases during journey reconstruction. For instance, if a customer contacts customer support on one day, receives a call back after two days, and sends a follow up message on the third day, the journey could be either a single unresolved journey or three separate contacts, depending on whether the issue is resolved. When available, reliable case closure flags in CRM systems provide the clearest signal for delimiting episodes [7]. Furthermore, if case closure flags are not available, heuristic rules based on repeat contact windows and matching issue categories can be used to build and estimate episode boundaries. According to the Process Mining Manifesto, episode delimitation (the process by which case boundaries are defined) is one of the most technically challenging steps in preparing event logs for analysis and should be done by domain experts [10].

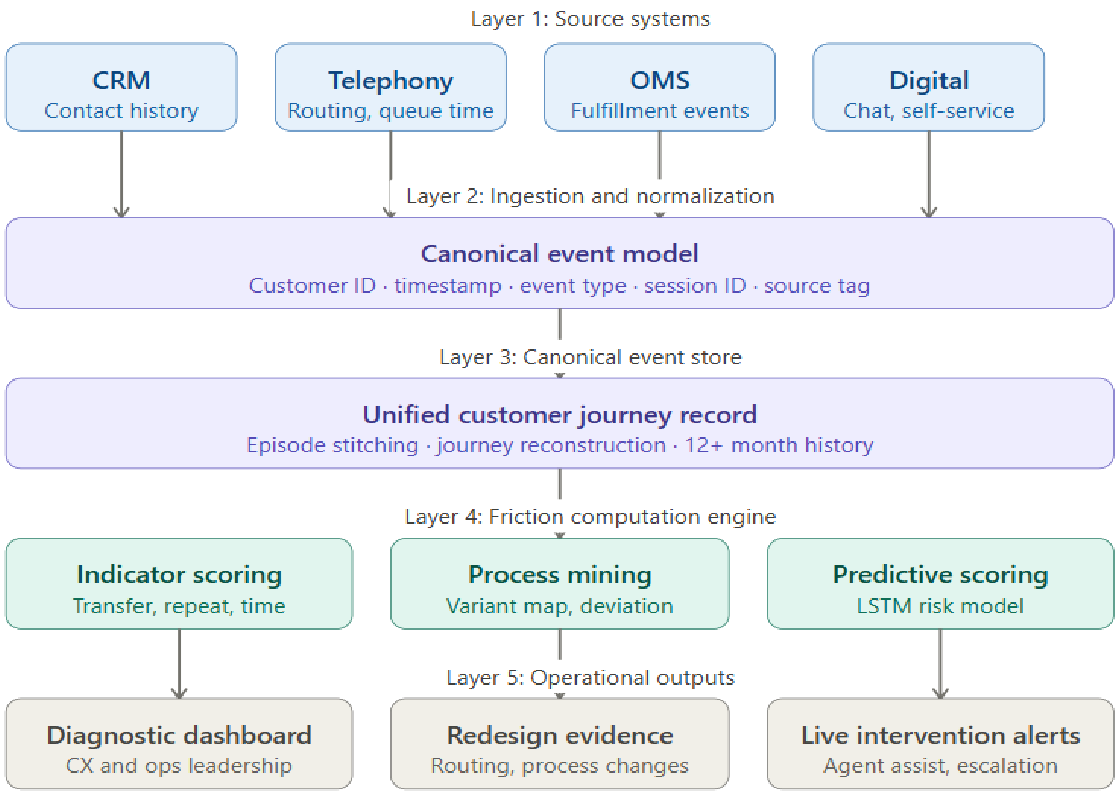

Figure 4: Data Flow Diagram Showing End-to-End Architecture [6, 10]

5. Analytical Methods for Friction Quantification and Diagnosis

5.1 Statistical Modeling of Friction Relationships

The first analytical objective is establishing which operational indicators most strongly predict customer satisfaction outcomes. Multivariate regression provides the primary method. By regressing satisfaction scores against friction indicator values drawn from the same journeys, it becomes possible to estimate the marginal contribution of each indicator to satisfaction variance [5]. Research in marketing analytics confirms that regression-based attribution in data-rich service environments can identify which process variables carry the highest explanatory power for customer outcome measures, enabling prioritization of improvement efforts [5].

Regression results should be validated across service type segments. The relationship between friction and satisfaction is not uniform across all customer interaction types. A high-complexity technical support case carries a very different friction tolerance profile than a routine order status inquiry [1]. Segmented models, built separately for interaction categories, produce more actionable coefficients than a single aggregate model. The use of regression for causal attribution in service contexts requires careful attention to confounding, since customers who contact support more frequently may differ systematically from those who do not [14]. Causal inference methods, including matching and instrumental variable approaches, can be applied to produce estimates of the effect of specific friction conditions on satisfaction outcomes that are more defensible than unadjusted correlation-based results [14].

5.2 Process Mining and Journey Pattern Analysis

Regression identifies which indicators matter. Process mining reveals where in the journey they manifest and under what structural conditions. Process mining algorithms reconstruct the actual service paths customers follow through the organization, derived directly from event logs rather than assumed workflow documentation [6]. The output is a variant map: a visual and computational representation of the actual distribution of journey paths, annotated with frequency and performance data.

High-friction variants emerge as identifiable patterns within the variant map. A variant in which customers follow a three-transfer routing path before reaching final resolution will display elevated total interaction time and low first-contact resolution rates [10]. The Process Mining Manifesto establishes conformance checking, comparing actual process behavior to designed process models, as one of the core analytical tasks enabled by event log analysis [10]. Applied to customer journey data, conformance checking reveals the gap between the intended service process and the process customers actually experience, which is itself a direct measure of structural friction. Process mining also surfaces deviating cases, journeys that do not conform to any dominant pattern, which often represent the highest-friction and most operationally complex interactions [6].

Analytical Technique	Primary Application	Key Output	Limitation
Multivariate Regression	Quantify relationships between friction variables and satisfaction scores	Coefficient weights, R-squared values	Assumes linear relationships; confounding risk
Clustering and Segmentation	Group journeys by structural friction profiles	Friction segments, centroid profiles	Requires labeled training data
Process Mining	Reconstruct actual service paths from event logs	Variant maps, deviation reports	Sensitive to log data quality
Survival Analysis	Model time-to-resolution across journey types	Hazard functions, median resolution time	Requires dense temporal data
LSTM-based Predictive Monitoring	Predict remaining cycle time and outcome for in-progress cases	Real-time risk scores, next-event predictions	Computationally intensive; requires large labeled datasets

Table 2: Analytical Techniques for Customer Journey Friction Modeling [5, 6, 11, 14]

5.3 Predictive Friction Monitoring

Beyond diagnosis, an advanced friction modeling capability supports prediction. Predictive business process monitoring addresses the goal of estimating, early in a running case, the probability of a specific outcome or the expected remaining time to completion [11]. Applied to customer journey friction, this means using early interaction signals to flag cases at risk of becoming high-friction before they have run their full course.

Research using Long Short-Term Memory neural networks for predictive process monitoring demonstrates that sequence-based models can achieve meaningful accuracy in predicting remaining cycle time and case outcomes from partial event traces [11]. The LSTM architecture is particularly suited to this problem because customer journey event logs are inherently sequential: each event in a journey updates the probability distribution over possible future trajectories. Training such a model requires a historical dataset of completed journeys with labeled outcome variables, which a mature friction indicator framework will generate as a byproduct of ongoing operational analytics [11].

The practical output of a predictive monitoring system is a real-time friction risk score, assigned to each in-progress interaction, that can trigger graduated intervention responses. This transforms friction management from a retrospective analytical exercise into a live operational control, with direct implications for service staffing, routing logic, and agent assist tooling [17].

6. Operational Applications and Intervention Design

6.1 Process Redesign Driven by Friction Evidence

The most direct application of friction modeling is the identification of service process bottlenecks with sufficient specificity to guide redesign. When transfer frequency analysis reveals that a specific routing rule consistently directs customers to a department lacking the authority or information to resolve their issue, the solution is a targeted routing logic change rather than a broad training program [13]. Research on telephone call center operations establishes that routing design, specifically the match between customer demand characteristics and agent skill sets, is the primary driver of first-contact resolution rates [13]. Friction model outputs make it possible to identify routing mismatches at scale and with statistical confidence, rather than relying on supervisor observation or agent-reported difficulty.

Process redesign decisions should be validated against a counterfactual estimate of friction reduction. Counterfactual effects can be simulated for routing changes, by estimating the friction effects of such changes based on past data. For instance it can be calculated what the percentage of transfers and the total time to resolution would have been for the number of calls impacted by the change [14]. Counterfactuals based on causal inference can frequently be employed in non-experimental settings of process improvement projects, where the treatment effects can be credibly estimated without experimental data [14].

6.2 Proactive Intervention Architecture

Real-time friction scoring enables an intervention architecture that is fundamentally different from traditional escalation models. Rather than waiting for a customer to explicitly request escalation, or for a supervisor to notice a struggling interaction, the system detects friction accumulation signals and triggers appropriate responses during the live interaction [11]. Research on human-AI collaboration in work settings provides a relevant design framework. In general, best practice for human-AI systems is that humans are in control in ambiguous/complex situations, while AI provides decision support. In the case of reducing contact center friction, the human decides how to respond to friction, with access to AI-generated risk scores as decision support for agents and supervisors [19].

Intervention options can be stratified by friction severity. If there is low friction risk, the system may surface contextual knowledge base articles or recommended resolution scripts to the agent. In moderate friction risk, the system may perform a soft handoff to a specialist resource. At high risk, it may initiate a supervisor review or activate a retention protocol. This stratification principle is consistent with the tiered escalation architectures described in service operations research for managing high-complexity call types in multi-skill contact center environments [13].

6.3 Omnichannel Consistency and Cross-Channel Friction

Channel switching introduces a different friction profile that needs to be designed for. The longer the customer is passed across multiple channels to resolution, the more friction is unnecessarily introduced at each switch [1]. The literature on the consumer decision journey identifies the post-purchase service experience as a critical touchpoint that shapes future loyalty and re-entry into the decision journey [8]. Service failures at channel boundaries are particularly damaging at this stage because they occur after customers have already invested effort in initiating a resolution process, where context is lost and they must re-explain their issue [8].

Addressing cross-channel friction requires both a data solution and a process solution. On the data side, a common context record is kept across all contact channels so that the customer's history and current state of issue is visible to any agent handling the contact regardless of channel [7]. On the process side, warm handoff protocols that explicitly transfer accumulated context reduce the re-establishment burden on both customers and agents. Research on CRM architecture confirms that cross-channel data integration, enabling a unified customer interaction record, is among the highest-value technical investments available to service organizations [7].

7. Implementation Considerations and Organizational Prerequisites

7.1 Governance and Stakeholder Alignment

Friction modeling tends to be used alongside CEM and operational analytics functions, which may also be differently governed with different leaders, measures of performance, and models of data ownership. Successful implementation requires a governance structure that brings them into a shared accountability framework. Research on big data analytics in marketing contexts identifies organizational alignment, specifically the coordination between marketing, IT, and operations functions around shared analytical objectives, as the primary organizational prerequisite for realizing value from customer data investments [4]. A shared friction KPI framework is the practical instrument of alignment. When CX and operations teams are evaluated against the same friction metrics, improvement initiatives become a shared operational objective rather than the exclusive responsibility of one function. This structural alignment produces more durable improvements than unilateral CX program interventions and is consistent with the finding in customer journey research that cross-functional coordination is required to manage experience quality across the full set of touchpoints a customer encounters [1].

7.2 Implementation Challenges and Mitigations

Several recurring challenges constrain friction modeling implementations. Table 3 summarizes the primary challenge domains, their specific manifestations, and the mitigations most likely to be effective [4, 10].

Challenge Domain	Core Problem	Recommended Mitigation
Data Integration	Siloed systems generate incompatible schemas and event structures	Implement a canonical data model via an integration layer or event bus
Data Quality	Incomplete records, timestamp mismatches, and missing channel linkages	Define SLAs for data completeness; automate anomaly flagging
Organizational Alignment	Operations and CX teams use different KPIs and ownership models	Establish joint governance with shared friction KPI dashboards
Analytical Capability	Insufficient internal expertise to build and maintain friction models	Invest in modular tooling; partner for capability development
Change Management	Process redesign triggers resistance from frontline teams	Pilot in low-risk segments and communicate outcomes with frontline staff

Table 3: Implementation Challenges, Manifestations, and Recommended Mitigations [4, 10]

Data integration complexity is consistently the highest-effort challenge, not because the technical patterns are novel but because enterprise data environments accumulate technical debt and schema inconsistencies over time [3]. Phased integration, e.g., starting with the two or three source systems that contribute the most valuable indicators, avoids the risk of trying to integrate all source systems before providing analysis results. Data extraction and data transformation are the most labor-intensive parts of a process mining project according to the Process Mining Manifesto, and iterative scoping is a recognized approach to control this [10].

Another barrier is organizational resistance to process redesign, which has received less attention. Friction modeling produces evidence that specific processes are failing. The teams responsible for those processes may experience analytical findings as criticism rather than diagnosis. Communication strategies that frame friction data as system evidence rather than performance assessment, and that engage frontline teams in interpreting and acting on findings, significantly reduce this resistance [4].

7.3 Phased Implementation Roadmap

A phased implementation reduces risk and accelerates time to value. Phase one focuses on foundational data integration: establishing the canonical event model, connecting the highest-priority source systems, and building the journey reconstruction logic. The output of this phase is a validated historical friction dataset covering at least twelve months of interaction volume [6].

Phase two develops the core analytical layer: regression models quantifying friction-to-satisfaction relationships, process mining outputs identifying high-friction variants, and initial composite friction scoring at the journey level. This phase should produce a friction diagnostic dashboard visible to both CX and operations leadership [5]. The execution phase (phase three) includes the implementation of the predictive scoring model and friction alerts in the agent tooling, as well as the implementation of the interventions described in phase two. The team also implements the measurement infrastructure in this phase to measure whether the redesigned processes meet the friction reduction goal [11].

8. The Role of Artificial Intelligence in Friction-Aware Service Systems

8.1 AI-Assisted Agent Performance and Friction Reduction

The use of AI-based assistance tools in contact center environments has made a measurable impact on service friction. Empirical research found that the staggered introduction of a generative AI conversational assistant across a large population of customer support agents increased worker productivity, measured as issues resolved per hour, by 15% on average [20]. This drives productivity up and, thus, total interaction time down, one of the main signs of operational friction. Faster resolution at the agent level translates to shorter cycle times for customers and a reduction in the temporal dimension of friction.

The distribution of performance effects observed in that study carries important implications for friction model design. Less experienced and lower-skilled workers improved both the speed and quality of their output, while the most experienced and highest-skilled workers saw small gains in speed and small declines in quality [20]. This pattern suggests that AI assistance has the greatest friction-reduction value in service segments handled by newer or less specialized agents, which are precisely the segments where transfer frequency and repeat contact rates tend to be elevated. The study also found that AI assistance facilitated worker learning over time, particularly improving English fluency among international agents, which suggests that friction reductions from AI adoption may compound as agent capability develops [20].

8.2 Human-AI Collaboration in Service Delivery

The service design of AI systems needs to consider the degree of automation versus human decision-making within the service. Research on human-AI collaboration identifies the challenge of maintaining meaningful human agency in systems where AI recommendations are generated in real time and under time pressure [19]. In the contact center context, an agent presented with an AI-generated friction risk score and a recommended action must be able to evaluate that recommendation against contextual information that the model may not have captured. This requires the design of an interface that frames AI output as decision support but gives the agent the ability to dismiss or modify the recommendation [19].

Research on AI in service also highlights the dual character of AI adoption at the workforce level [17]. AI-based tools that reduce friction for customers may simultaneously displace or restructure the work of service agents. Historically, people have considered service jobs more resistant to automation than manufacturing roles because they rely on contextual understanding and spontaneous interactive communication [17]. However, the capabilities of large language model-based tools are testing this assumption. The empirical finding shows that a significant proportion of tasks in high-paying service roles can be automated using current technology, suggesting that the boundary between automatable and non-automatable service work is shifting [17]. Friction modeling systems that deploy AI at scale should account for these workforce implications in their design and implementation planning.

8.3 AI-Driven Causal Attribution in Friction Systems

A further application of AI in friction modeling involves moving beyond statistical association toward causal understanding of friction drivers. Standard regression analysis establishes correlations between friction indicators and satisfaction outcomes but does not identify the causal mechanisms through which specific process conditions produce specific customer responses [15]. Causal inference frameworks, including structural causal models and directed acyclic graphs, provide the formal tools for reasoning about causal structure in observational data [15].

The practical implication for friction modeling is that improvement initiatives targeting correlated indicators may not produce the expected satisfaction gains if those indicators are symptoms of a deeper structural cause rather than causes themselves [14]. For instance, routing design, agent skill distribution, or system access constraints may cause a high transfer frequency score. Intervening on routing logic without addressing underlying skill distribution may produce only partial friction reduction [13]. Causal attribution analysis, guided by structural causal models estimated from operational data, enables improvement teams to identify intervention points that address root causes rather than observable symptoms [15].

Conclusion

Customer experience improvement programs that rely exclusively on sentiment metrics are constrained by a fundamental measurement limitation: they observe outcomes without examining the processes that produced them. Customer Journey Friction Modeling reorients the diagnostic work by treating operational process signals as primary evidence. Transfer frequency, repeat contact rates, total resolution time, and channel switching behavior are direct records of the effort customers expended navigating a service system. Building analytical infrastructure around these signals produces a more precise, more actionable, and more scalable approach to experience improvement than survey aggregation alone can support. The integration of process mining, predictive monitoring, and AI-assisted intervention design extends the framework from retrospective analysis toward live operational control. At the same time, the organizational prerequisites for realizing this capability, data integration, cross-functional governance, and careful human-AI collaboration design are as important as the technical components. The evidence that AI-based tools can reduce friction and improve agent performance is compelling, but the workforce and causal attribution implications of large-scale AI adoption in service environments warrant continued analytical attention. The organizations that build a rigorous operational foundation for friction measurement now are positioning themselves to realize the full potential of these capabilities as they mature.

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