Incorporating Offline and Call-Center Interactions into Digital Personalization: An Integrated Customer 360 Approach for B2C Sales Optimization

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Abstract

Digital personalization in consumer markets has largely been driven by data from web, mobile, and other online channels. At the same time, many B2C organizations continue to rely on call centers, branch networks, and face-to-face sales interactions that generate rich but fragmented information about customer preferences and constraints. This fragmentation can lead to inconsistent treatment, misaligned incentives across channels, and suboptimal resource allocation in sales and service operations. Bridging the information gap between online and offline interactions therefore remains a central challenge for building a coherent view of the customer. This paper examines an integrated Customer 360 approach in which offline and call-center interactions are explicitly incorporated into digital personalization logic for B2C sales optimization. The focus is on the representation, integration, and use of heterogeneous interaction data rather than on any specific software platform. Offline contacts and call-center events are embedded into a shared temporal and semantic space, enabling joint modeling of exposure, response, and purchase behavior across channels. The proposed framework links a data architecture for Customer 360 with probabilistic models of customer state and optimization formulations for contact and channel policies. It emphasizes how call outcomes, agent annotations, and branch visit patterns can adjust latent customer-state variables that drive digital personalization decisions. The discussion covers modeling detail, implementation aspects, and an illustrative scenario, while adopting a neutral stance on design choices so that the framework can be adapted to differing B2C contexts and levels of data maturity.

1 Introduction

B2C firms increasingly interact with customers across many channels that include web sites, mobile applications, email, messaging platforms, call centers, and offline locations such as branches or stores [1]. Digital personalization strategies typically use online behavioral and transactional data to adapt recommendations, offers, and contact timing for each customer. However, for many organizations, a substantial fraction of sales conversations, service resolutions, and high-value interactions still occur via call-center agents or in offline settings. The information generated during those contacts often remains weakly integrated with digital analytics and is sometimes stored in unstructured or siloed systems that are difficult to use in personalization models. As a result, online decision engines may react as if those contacts never occurred, or they may use only coarse summary indicators that do not capture the nuance of the interactions.

Customer 360 initiatives aim to consolidate data from multiple sources into a unified representation of the customer, often combining profiles, transaction histories, behavioral traces, and external data [2]. In practice, such initiatives can remain descriptive, providing dashboards and query capabilities without fully influencing the operational personalization logic that drives day-to-day customer contact. Bringing Customer 360 into the core of B2C sales optimization requires explicit modeling of how offline and call-center events enter into decisions about when and how to contact customers through each channel. These decisions must balance sales uplift, service quality, capacity constraints, and regulatory or preference-based contact limits.

The integration of offline and call-center interactions into personalization raises modeling and operational questions that go beyond simple feature concatenation. Offline and call-center channels often have different cost structures, response dynamics, and measurement properties than digital channels [3]. Call outcomes may be captured through structured disposition codes, but the underlying dialogue, negotiation, and persuasion are partially observed. Offline visits may be missing or delayed in data feeds, introducing latency and uncertainty. Moreover, the allocation of customers to call-center agents and offline sales staff introduces additional layers of decision making that interact with digital personalization logic.

This paper develops a technical framework for incorporating offline and call-center interactions into an integrated Customer 360 approach for B2C sales optimization. The framework treats the customer as an evolving state that is updated by events in any channel and that drives probabilistic response and purchase processes [4]. Offline and call-center events enter the state dynamics as signals of intent, friction, or constraint. Digital personalization is then formulated as the optimization of contact and channel policies conditional on this state. The resulting structure allows organizations to subject their cross-channel strategies to quantitative analysis while preserving the flexibility to adjust modeling choices to their context.

The remainder of the paper proceeds by introducing a conceptual view of Customer 360 and omni-channel personalization, describing the data architecture required to represent offline and call-center events, specifying mathematical models for customer state and response, formulating optimization problems for contact and channel policies, and discussing implementation aspects and empirical evaluation. The conclusion summarizes the main elements and outlines directions for refinement in applied settings [5].

2 Customer 360 and Omni-Channel Personalization in B2C Sales

Customer 360 can be viewed as an attempt to represent each customer as a coherent entity whose observed behavior and attributes span multiple systems and touchpoints. In an omni-channel environment, a single customer may browse products on a mobile site, call a service line for clarification, receive follow-up emails, and ultimately complete a purchase in a branch. Each event leaves data traces that may vary in granularity, timing, and structure. The central question for personalization is how to encode these traces such that the customer's propensity to react to future stimuli can be inferred with sufficient accuracy and stability. Offline and call-center interactions add structure to that inference problem, because they often embody more explicit expressions of intent and constraint than many digital signals [6].

From a technical perspective, Customer 360 can be conceptualized as a high-dimensional state representation that is filtered and projected into the feature space used by personalization models. The state may include slowly moving attributes such as demographics or long-run value segments, medium-horizon features such as product holdings or tenure, and fast-moving indicators such as recent visits, calls, or complaints. An omni-channel perspective treats these indicators as arising from a single underlying behavioral process rather than from separate channel-specific processes. This suggests representing customer dynamics by a joint model in which the probability of future events depends on an evolving latent state influenced by all past interactions.

In many B2C contexts, call-center and offline interactions are associated with moments of high involvement, such as complex purchases, problem resolution, or complaints [7]. These events can strongly update beliefs about the customer's current and future behavior. For example, a recent complaint handled in the call center may signal increased churn risk or lower acceptance probability for new offers in the short term, even if browsing behavior or product holdings remain unchanged. Conversely, a consultation in a branch that results in a partial product uptake may reveal latent potential for cross-sell that is not yet evident in the digital trace. Capturing these updates requires a modeling strategy in which offline and call-center events are not treated as static explanatory variables but as triggers of state transitions.

A Customer 360 representation for omni-channel personalization also needs to account for the role of constraints and preferences [8]. Call-center logs may include explicit statements of contact preferences or objections, which should inform the admissible action set of digital personalization engines. Offline visits may reveal geographic or logistical constraints that affect the feasibility of certain offers or delivery options. Incorporating these signals into the state representation can reduce wasted contacts and align personalization with customer expectations, but it requires structured data capture and transformation pipelines that can translate unstructured notes or disposition codes into usable features.

The design of a Customer 360 state that integrates offline and call-center data must balance richness and parsimony. Very granular state variables may capture nuanced aspects of customer behavior but can be difficult to estimate and maintain, especially if some channels are sparsely observed [9]. Conversely, overly coarse state representations may fail to differentiate between customers who have similar digital footprints but very different offline histories. The approach developed in this paper adopts a layered view in which raw events from all channels are mapped into canonical interaction types, which are then summarized into interpretable state variables that feed into the modeling and optimization layers of the personalization system.

3 Data Architecture for Integrating Offline and Call-Center Interactions

An integrated Customer 360 approach requires a data architecture that can ingest, align, and transform events from digital channels, call centers, and offline points of presence. At the core lies a customer identity resolution mechanism that assigns events to persistent customer identifiers. In many organizations, offline and call-center systems use identifiers that differ from those used in digital channels, leading to fragmented histories. Even when identities can be reconciled, event timestamps, codes, and fields may not follow consistent standards [10]. An effective data architecture must therefore perform not only data consolidation but also harmonization of semantics across systems.

A practical representation starts from an interaction table in which each row corresponds to a time-stamped event associated with a customer. Columns identify the channel, event type, outcome, and any key attributes such as agent identifier, location, or product. Call-center logs typically provide structured outcome codes indicating whether a call was answered, abandoned, transferred, or resolved, as well as reason codes and, in some cases, quality measures. Offline events for branch visits or in-store interactions may be captured through appointment systems, point-of-sale logs, or manual entries [11]. These events can be mapped into canonical categories such as inquiry, complaint, opportunity, or closure. Digital events such as page views, clicks, or app sessions are already typically structured, but they may require aggregation to be comparable in temporal granularity to offline and call-center events.

For integration into personalization models, the raw interaction table is often transformed into sequences of events for each customer, along with derived features that summarize recent history. A state extraction process may compute rolling counts of interactions by type and channel, time since last contact, and simple indicators for specific combinations of events. Call-center and offline events can play a particular role in this process because they are relatively infrequent but potentially more informative [12]. A single extended call about a billing issue, for example, may carry more informational weight than many generic web visits. State extraction can therefore assign higher weights or specific feature roles to such events, either directly or via latent variable models.

Given that some channels are not continuously observed, the data architecture must handle missingness and irregular sampling. Offline visits and call-center calls may cluster around salient events, while digital traces can be nearly continuous for some customers and sparse for others. A uniform time grid, such as daily or weekly periods, can be used to aggregate events across channels and to align the state updates [13]. For each customer and period, the interaction table can be collapsed into a limited number of variables that indicate whether and how often each interaction type occurred. This aggregation provides a consistent input for temporal models without requiring that events from all channels be observed at every step.

Call-center systems often contain unstructured notes that document the content of conversations. While these notes are not the primary focus of this paper, they offer additional scope for enhancing the Customer 360 view. Text analytics can transform notes into indicators of topics, sentiment, and expressed constraints [14]. These indicators can then be fused with structured outcomes and digital behaviors to refine the state representation. The data architecture must support this fusion by maintaining links between raw notes, extracted indicators, and downstream features used in modeling and optimization.

Finally, the data architecture must address latency and update frequency. Digital events may be available in near real-time, while offline and call-center data may be subjected to batch ingestion and quality checks. To support coherent personalization decisions, the architecture should ensure that state updates triggered by offline or call-center events are propagated to the personalization engine within a timeframe consistent with the cadence of decisions [15]. This requirement may motivate separate online and offline feature stores, with mechanisms for incremental updates that incorporate new call-center and offline events as they arrive.

Channel	Interaction Type	Key Challenge
Digital (web/app)	Behavioral and transactional events	High frequency, low explicit intent
Call Center	Service, inquiry, complaint calls	Semi-structured, partially observed dialogue
Offline Branch	In-person consultations, purchases	Sparse events, latency in data capture

Customer 360 Element	Description	Integration Role
Identity Resolution	Linking identifiers across systems	Ensures unified customer timeline
Canonical Event Types	Standardized mapping of interactions	Enables cross-channel comparability
State Variables	Latent/observed features from history	Inputs to personalization models

Interaction Source	Data Properties	Modeling Implication
Digital Logs	Continuous and granular	Requires aggregation and smoothing
Call Dispositions	Structured codes and notes	Capture intent and constraints
Branch Visits	Event-based and delayed	Introduce uncertainty in state updates

Modeling Component	Offline/Call-Center Influence	Impact on Personalization
State Transition	Updates intent, friction, constraints	Alters predicted responsiveness
Feature Extraction	Weighted recent interactions	Adjusts action probabilities
Decision Policy	Channel feasibility limits	Shapes selection of contact channel

4 Mathematical Modeling of Customer States and Response

A central element of integrating offline and call-center interactions into digital personalization is the mathematical representation of the customer's evolving state. Let i index customers and t index discrete decision periods. For each customer i and time t, define a state vector s_{it} that summarizes the available information from all channels up to time t. The state may include observed attributes x_{it}, latent variables z_{it}, and counts or indicators of recent events. Formally, one may write

$$s_{it} = \big(x_{it}, z_{it}\big).$$

The observed component x_{it} can include aggregated measures of call-center and offline interactions, such as the number of complaints in a recent window, time since last call, and indicators of channel preferences. The latent component z_{it} captures unobserved propensities such as purchase intention or churn risk.

The transition of the latent state over time can be modeled as a stochastic process that depends on past state and actions [16]. Let a_{it} denote the action taken at time t, such as sending a digital offer, assigning a call-center follow-up, or making no proactive contact. A simple linear-Gaussian state transition for z_{it} can be written as

$$z_{i,t+1} = F z_{it} + G a_{it} + \eta_{it},$$

where F is a state evolution matrix, G is an action-effect matrix, and η_{it} is a noise term. Call-center and offline interactions enter the state transition through their influence on a_{it} and through components of x_{it} that summarize their occurrence. More flexible non-linear or non-Gaussian specifications can be adopted, but even this simple structure allows offline and call-center events to shift the latent state in systematic ways.

The customer response to actions is captured through an outcome variable y_{it}, which may represent purchase occurrence, value, or another event of interest. A common choice is a binary response model in which $y_{it} = 1$ indicates a purchase or positive outcome in period t. The conditional probability of response may be modeled using a logistic link as

$$p_{it} = \Pr(y_{it} = 1 \mid s_{it}, a_{it}),$$

$$p_{it} = \frac{\exp\big(\theta^\top f(s_{it}, a_{it})\big)}{1 + \exp\big(\theta^\top f(s_{it}, a_{it})\big)},$$

where $f(s_{it}, a_{it})$ is a feature function that can explicitly encode the presence and recency of offline and call-center events. The parameter vector θ is estimated from historical data. In this construction, call-center and offline events are not only covariates but also potential mediators of treatment effects, because they may be influenced by earlier actions and, in turn, affect future states and outcomes [17].

To capture the influence of call quality or offline interaction intensity, one may refine the feature function. Suppose that c_{it} denotes a call-related summary, such as the weighted count of recent calls, and o_{it} denotes an offline interaction summary. A parsimonious feature specification may take the form

$$f(s_{it}, a_{it}) = \big(x_{it}, c_{it}, o_{it}, a_{it}\big),$$

which keeps the equation width modest while allowing for interactions between channels and actions. Additional non-linearities can be introduced through basis expansions of these components [18].

Beyond static response models, it is often useful to consider the cumulative value generated over a horizon. Define a per-period reward r_{it} that reflects realized revenue, cost of actions, and possibly non-monetary metrics such as satisfaction. The expected cumulative discounted reward for customer i under a policy π can be expressed as

$$V_i^\pi = E\Big[\sum_{t=1}^{T} \gamma^{t-1} r_{it} \;\Big|\; \pi\Big], [19]$$

where $\gamma \in (0, 1)$ is a discount factor. A policy π maps states to actions, and the goal of B2C sales optimization is to identify a policy that yields high value when evaluated over the customer base. Offline and call-center interactions influence V_i^π both through their effect on immediate reward and through their long-run impact on state and future responses.

Estimating the models that underlie p_{it}, z_{it}, and V_i^π requires dealing with the fact that actions are not randomly assigned. Call-center interventions and offline outreach may target specific customers based on rules that depend on observed or unobserved characteristics. This creates selection that must be addressed to avoid biased estimates of channel effects. Techniques such as inverse-propensity weighting, doubly robust estimation, or structural modeling can be applied in this context [20]. In each case, offline and call-center data play a dual role as sources of information about customer behavior and as components of the treatment assignment mechanism.

5 Optimization of Contact Policies and Channel Allocation

Once a model of customer state and response is available, the next step is to formulate the optimization problem associated with contact policies and channel allocation. Consider a planning horizon of T periods and a set of channels that include digital, call-center, and offline options. For each customer i and time t, the decision maker chooses an action a_{it} from an action set $\mathcal{A}$ that may depend on the state s_{it}. The objective is to maximize an expected measure of cumulative value subject to constraints on contact frequency, channel capacity, and budgets.

A generic formulation of the optimization problem can be written as [21]

$$\max_{\pi} \sum_i V_i^\pi,$$

where π is a policy that maps states to actions and V_i^π is the value function defined previously. Practical implementations often approximate this global optimization through myopic or limited-horizon decisions that use predicted response probabilities and values. Let $\hat{p}_{it}(a)$ denote the predicted probability of a positive outcome if action a is taken in state s_{it}, and let $v_{it}(a)$ denote the associated expected value net of channel cost. A simple scoring rule for ranking customers for a given channel m at time t can be expressed as

$$u_{it}^{(m)} = \hat{p}_{it}(a^{(m)}) v_{it}(a^{(m)}),$$

where $a^{(m)}$ represents an action that uses channel m. Offline and call-center interactions enter these scores through their effect on s_{it}, and thus on $\hat{p}_{it}(a)$ and $v_{it}(a)$.

Capacity constraints for channels are typically imposed at aggregate levels. For the call center, there may be a maximum number of outbound calls that can be made in a period, while for offline branches there may be limits on appointments or in-person consultations. Let $N_t^{(m)}$ denote the maximum number of customers that can be contacted through channel m at time t. A simple allocation rule is to rank customers by $u_{it}^{(m)}$ and select the top $N_t^{(m)}$ for that channel, subject to contact policy constraints such as time since last contact. The optimization problem then becomes one of selecting subsets of customers across channels that respect these constraints [22].

A more explicit representation can be obtained by introducing binary decision variables. Let $d_{it}^{(m)} \in \{0, 1\}$ indicate whether customer i is assigned to channel m at time t. A static allocation problem for a single period can be written as

$$\max_{d} \sum_i \sum_m u_{it}^{(m)} d_{it}^{(m)},$$

subject to

$$\sum_i d_{it}^{(m)} \leq N_t^{(m)},$$

$$\sum_m d_{it}^{(m)} \leq 1.$$

The first constraint enforces channel capacities, while the second ensures that each customer receives at most one contact in the period. Offline and call-center contact costs or priorities can be reflected in the utilities $u_{it}^{(m)}$ or in additional constraints that limit the fraction of contacts allocated to specific customer segments.

Dynamic optimization formulations treat the state transitions explicitly and seek policies that consider long-run effects [23]. This naturally leads to Markov decision process representations in which the tuple (s_{it}, a_{it}, r_{it}) defines a Markovian structure. The Bellman equation for an optimal value function $V(s)$ can be written as

$$V(s) = \max_{a \in \mathcal{A}} \Big\{ R(s, a) + \gamma[24] E\big[V(s') \mid s, a\big] \Big\},$$

where $R(s, a)$ is the expected immediate reward and s' is the next state. In this formulation, offline and call-center actions are elements of $\mathcal{A}$, and their influence on future states and rewards is captured through the transition probabilities and reward function. Computing exact optimal policies for large state spaces can be difficult, so approximate dynamic programming or reinforcement learning methods are often used.

Offline and call-center interactions can also be framed as constraints that restrict digital personalization [25]. For example, customers who have recently received a call about a specific product may be excluded from receiving digital ads for the same product within a cooling period. This can be represented by constraints on allowable actions. Let $g(s_{it})$ denote a function that indicates whether certain actions are admissible. The feasible action set at time t becomes

$$\mathcal{A}(s_{it}) = \{a \in \mathcal{A} : g(s_{it}) = 1\}.$$

Call-center and offline events contribute to $g(s_{it})$ by marking states in which certain contacts would violate policies or preferences. The optimization problem then proceeds as before but with this restricted action set [26].

Implementation Area	Requirement	Key Consideration
Data Engineering	Cleaning, mapping, deduplication	Latency, completeness, drift detection
Feature Extraction	Constructing call/offline features	Distinction between intent and service events
Model Integration	Reliable state computation	Alignment with cadence of decision cycles

Evaluation Mode	Method	Insight
Offline Testing	Historical replay and fit metrics	Improvement from call/offline features
Online Testing	Randomized policy experiments	Incremental uplift from integrated view
Hybrid Testing	Partial randomization	Effect isolation under realistic constraints

Governance Domain	Focus	Practical Need
Privacy	Data minimization, access control	Compliance across channels
Attribution	Cross-channel contribution rules	Avoiding biased performance views
Consent Sync	Preference alignment across systems	Unified customer experience

6 Implementation Aspects and Empirical Evaluation

Implementing an integrated Customer 360 approach that explicitly incorporates offline and call-center interactions into digital personalization requires coordination between data engineering, modeling, and operations. From a system perspective, the state representation s_{it} and the associated feature extraction functions must be computed reliably and made available to personalization engines at the cadence of decision making. Call-center and offline data feeds must be cleaned, de-duplicated, and mapped into the canonical interaction schema, with particular attention to latency and completeness. Monitoring pipelines should track coverage of call and offline data across the customer base and over time to detect drift or gaps.

On the modeling side, the choice of functional forms for response and state transition models must balance interpretability, flexibility, and computational cost. Parametric models such as logistic regression or generalized linear models offer transparency and ease of estimation but may not capture complex interactions between channels and states. Non-parametric or machine learning models can provide additional flexibility at the cost of interpretability [27]. In either case, the definition of features that summarize offline and call-center interactions is crucial. These features must capture meaningful distinctions, such as whether a call was initiated by the customer or by the firm, whether an offline visit involved a sales conversation or a service issue, and whether the outcome was satisfactory or unresolved.

Evaluation of the integrated approach can proceed through a combination of offline and online methods. Offline evaluation uses historical data to compare the predictive performance of models with and without offline and call-center features. For example, one may estimate two response models, one based only on digital data and another that adds offline and call-center features, and compare predictive accuracy or calibration [28]. A simple measure might involve the difference in log-likelihood or a related metric. Denote by ℓ_{dig} the average log-likelihood for a purely digital model and by ℓ_{full} that for the full model. An improvement measure can be written as

$$\Delta\ell = \ell_{\text{full}} - \ell_{\text{dig}}.$$

A positive value of $\Delta\ell$ indicates that including offline and call-center data improves the fit according to this metric.

Online evaluation involves controlled experiments in which personalization policies that use the integrated Customer 360 view are compared against baseline policies [29]. Randomized assignment of customers to policies

Sensitivity Factor	Variation	Impact on Personalization
Latency in Call Data	Delayed state updates	Reduced decision accuracy
Feature Granularity	Coarse vs refined sets	Changes in predicted responsiveness
Operational Constraints	Channel capacity shifts	Altered optimal contact allocations

helps address confounding, but practical constraints may limit the scope of experimentation, especially for call-center and offline channels where capacity and fairness considerations arise. Hybrid evaluation designs, in which digital personalization is randomized while call-center and offline operations follow standard procedures, can still reveal the incremental effect of using offline and call-center data in digital decision making. In such designs, uplift models can be estimated to capture the heterogeneity of treatment effects across customers with different offline and call histories.

Implementation also requires addressing governance and compliance aspects. Offline and call-center data often include sensitive information about customer circumstances, preferences, and complaints [30]. Integrating these data into personalization systems must comply with privacy regulations and internal policies. This may require minimization of data, restriction of access, and transparent documentation of how features derived from these data are used in decision making. Mechanisms for customer consent and preference management should be aligned across channels so that a change in preference recorded in the call center is reflected in digital personalization and vice versa.

Finally, practical deployment must deal with the evolution of models and policies over time. As call-center and offline operations change, or as new digital channels emerge, the data generating process for interactions will shift [31]. This necessitates continuous monitoring of model performance, retraining schedules, and potentially the redefinition of state variables. Drift detection methods can be applied to key metrics such as response rates, acceptance probabilities, and value per contact. If a decline in performance is observed, analyses can help determine whether the cause lies in changes in customer behavior, in call-center or offline practices, or in external factors that influence the effectiveness of personalization strategies.

7 Empirical Illustration and Sensitivity Considerations

To illustrate the implications of integrating offline and call-center interactions into digital personalization, consider a setting in which a B2C firm uses outbound email, app notifications, outbound calls, and branch appointments to promote a portfolio of products. The firm maintains historical records of digital interactions, call-center contacts, and branch visits, and it has implemented a Customer 360 data layer that aligns these events at the customer level [32]. For the purpose of this illustration, suppose that the firm is interested in optimizing weekly contact policies for a focal product while respecting channel capacities and customer preferences.

Historical data can be used to estimate a response model of the form described earlier, in which the probability of purchase in a given week depends on the Customer 360 state and the chosen action. Let $\hat{p}_{it}(a)$ denote the fitted probability for action a in state s_{it}. Suppose that the firm derives an expected value per purchase w_{it} that may vary across customers based on product configuration or potential volume. A simple expected value measure for action a can then be defined as

$$v_{it}(a) = \hat{p}_{it}(a) w_{it}.$$

This value measure can be combined with channel costs and capacity constraints to construct weekly contact plans. Offline and call-center data influence $v_{it}(a)$ through their role in shaping s_{it} and therefore the predicted probabilities.

To assess the marginal contribution of offline and call-center data, one can construct two sets of policies [33]. The first policy uses only digital features in the state representation and response model, while the second policy uses the full Customer 360 state including offline and call-center features. Simulated or historical replay analysis can then be used to compare the expected value achieved by the two policies under various scenarios. For instance, if the simulated environment uses the full model as the ground truth, one can compute expected value trajectories for each policy and examine their difference. Let J_{full} denote the average per-customer value under the policy that uses the full state and J_{dig} denote the corresponding value for the digital-only policy. A simple measure of relative difference is

$$\Delta J = [34] J_{\text{full}} - J_{\text{dig}}.$$

The sign and magnitude of ΔJ will depend on the strength of the information contained in offline and call-center data and on operational constraints.

Sensitivity analysis can explore how the benefits of integration vary with key parameters. For example, the value of call-center data may depend on the time lag between call occurrence and its availability in the personalization engine. If state updates are delayed, the system will base decisions on incomplete information about recent calls.

One can simulate different latency levels by truncating or lagging call-center features in the historical data before training and evaluating models. Let L denote the number of periods of delay [35]. A performance measure $J(L)$ can be computed for each L, and the sensitivity of value to latency can be summarized by differences such as

$$\Delta J(L) = J(0) - J(L),$$

where $J(0)$ corresponds to minimal latency. This analysis can guide investment decisions in data engineering by quantifying the impact of reducing latency for call-center and offline data feeds [36].

Another dimension of sensitivity concerns the definition of state variables that summarize offline and call-center interactions. Alternative feature sets can be constructed that vary in granularity or weighting of events. Some definitions may emphasize recency, while others focus on cumulative history or intensity of interactions. Models can be re-estimated for each feature set, and corresponding policies can be derived and evaluated. The resulting performance differences can suggest whether more refined state representations yield meaningful gains or whether simpler summaries are sufficient [37]. This process also helps identify which aspects of offline and call-center behavior are most predictive and thus most important to capture reliably in data collection.

8 Organizational, Governance, and Change Management Considerations

Integrating offline and call-center interactions into a Customer 360 framework for digital personalization does not occur only at a technical level; it also interacts with organizational structures, governance arrangements, and change management practices. Many B2C firms operate with distinct teams responsible for digital marketing, call-center operations, branch or store management, and data and analytics. These teams may have separate objectives, performance indicators, and reporting lines. A Customer 360 initiative that alters how offline and call-center data are used in digital personalization can therefore modify perceived ownership of customers, campaigns, and outcomes [38]. To avoid misalignment, organizational roles and responsibilities need to be clarified so that decision rights over model design, channel rules, and optimization objectives are explicit and compatible with the incentives of each function. This does not require a single ideal structure, but it does require that local objectives, such as call-center handle-time targets or branch sales quotas, are reconciled with cross-channel optimization logic that may reassign contacts across channels.

Governance mechanisms provide a way to coordinate these interests. A governance arrangement for an integrated Customer 360 system typically involves a steering group or committee that includes representation from marketing, sales, call-center operations, branch leadership, analytics, technology, and compliance. The function of such a body is not only to approve models or campaigns but also to define high-level principles for how offline and call-center interactions are reflected in personalization logic [39]. Examples include agreeing on cooling-off periods after certain call outcomes, setting upper bounds on multi-channel contact frequencies, and clarifying rules for channel precedence in specific scenarios. Governance documents can codify these principles so that modeling and optimization choices are anchored in policies that are transparent to operational teams and auditable by internal or external stakeholders.

A central governance question concerns the definition of success metrics. Digital marketing teams may be accustomed to metrics such as open rates, click-through rates, and digital conversion rates, while call-center and offline operations may focus on measures such as first-call resolution, average handle time, branch footfall, and in-person sales. When offline and call-center interactions are incorporated into digital personalization, the outcome of a decision can manifest in multiple channels [40] [41]. A digital contact may prompt a customer to call the contact center or visit a branch rather than complete the purchase online. If evaluation metrics give full credit for sales only to the channel in which the transaction is recorded, digital personalization that deliberately anticipates and leverages offline and call-center follow-up may appear underperforming from a purely digital perspective. Governance can mitigate this by defining attribution rules that recognize cross-channel paths and by designing composite metrics that capture total customer value across channels rather than treating them in isolation.

Change management plays a significant role in how call-center agents and offline staff perceive and adapt to Customer 360 driven personalization. Agents may be presented with prompts or recommendations that incorporate digital history and model predictions [42]. Branch staff may receive prioritized lists of customers for proactive outreach based on integrated state representations. If these recommendations are not perceived as credible or useful, adoption is likely to be partial, and the feedback loop between offline behavior and digital personalization will be weakened. Change management practices such as involving frontline representatives in the design of workflows, explaining model inputs at a level appropriate for non-specialist users, and creating channels for feedback about the plausibility and usefulness of recommendations can improve alignment between model outputs and operational reality. Training that illustrates how offline and call-center information affects digital decisions can also support understanding and trust.

The interaction between automation and human discretion is another area where organizational and change-management issues arise [43]. Integrated Customer 360 systems may compute recommended actions or policies that are then presented to agents or digital orchestration engines. In some settings, call-center agents may have the discretion to override recommendations based on their own judgment, while in others they may be expected to follow them except in well-defined exceptional cases. Governance structures can set boundaries on where discretion is encouraged, where it is restricted, and how overrides are logged and analyzed. Over time, patterns in overrides may reveal systematic gaps in the modeling assumptions or data, especially around offline and call-center contexts that are not fully captured in the current state representation. Treating human judgment as a complementary source of information rather than as noise can support iterative refinement of the system [44].

Incentives and performance management systems influence how staff respond to an integrated Customer 360 framework. For example, call-center incentives may emphasize minimizing call length or maximizing the number of calls handled, which can conflict with deeper engagement that aims to gather information useful for personalization or to address underlying issues that would otherwise produce repeated contacts. Similarly, branch staff may be evaluated primarily on immediate sales, even when the personalization system suggests follow-up actions that prioritize long-run relationship building. Aligning incentives with the objectives embedded in the optimization models can be challenging but is important for consistency. This alignment may involve adjusting scorecards, introducing balanced metrics that include indicators of cross-channel collaboration, or at least ensuring that personalization-driven interventions do not inadvertently penalize staff in one channel for actions that benefit outcomes measured in another.

Data governance and stewardship are particularly relevant once offline and call-center data are used more intensively in personalization [45]. The content of calls and in-person interactions can include sensitive information about financial circumstances, health conditions, or other personal details. While not all of this information is captured or processed, governance must establish clear rules about what data can be used for modeling and under what conditions. Data minimization principles may limit the retention or usage of certain fields, and anonymization or masking approaches may be used where feasible. Role-based access control can restrict which staff can see specific categories of data, and audit trails can document queries and usage. When integrating offline and call-center data with digital traces, governance frameworks also need to consider differential regulatory requirements across jurisdictions and product types, which may lead to channel- or region-specific configurations of the Customer 360 architecture [46].

Communication with customers about the use of their data is another aspect of governance that affects the design and acceptance of integrated personalization. Call scripts, branch disclosures, and digital privacy notices may need to provide consistent information about how interaction data are used to improve services and offers. Preference management processes should allow customers to specify not only whether they wish to receive marketing communications but also through which channels and under what conditions. If a customer opts out of certain types of tracking or personalization in digital channels, the organization must determine how this affects the use of offline and call-center information, and vice versa. Implementing these decisions in the Customer 360 data and modeling layers may require flags and filters that restrict the inclusion of certain data in model training or decision logic [47].

The source and maintenance of analytical expertise are also an organizational consideration. An integrated Customer 360 approach that explicitly models offline and call-center interactions requires skills in data engineering, statistical modeling, optimization, and software implementation. Organizations must decide whether these capabilities will reside in a centralized analytics team, within specific business units, or in a hybrid model. Centralized teams may offer economies of scale and consistency in methods, but they can be distant from the operational realities of call-center or branch environments. Decentralized teams may be closer to the business but may face challenges in maintaining methodological coherence and shared infrastructure [48]. Governance can support either configuration by providing common standards, shared libraries, and forums for coordination without prescribing a single organizational form.

Vendor and platform choices introduce another layer of organizational and governance issues. Some firms rely on packaged customer data platforms, campaign management tools, and call-center systems that offer built-in integrations and modeling capabilities. Others develop custom solutions that combine internal data warehouses with bespoke modeling and optimization components. The extent to which offline and call-center interactions can be integrated into digital personalization may depend on the flexibility of these platforms and on contractual arrangements with vendors [49]. Governance bodies may need to evaluate trade-offs between adopting out-of-the-box capabilities that support a limited set of integrated use cases and investing in custom development to achieve deeper or more specific integration. These decisions can have implications for resource allocation, time-to-value, and long-term maintainability of the Customer 360 system.

Finally, change management must account for the iterative nature of integrated personalization. The initial deployment of models that leverage offline and call-center data will likely reveal gaps in data quality, process integration, and organizational readiness. Feedback mechanisms that collect information from users, monitor key performance indicators, and track incidents related to data or decisions can inform successive releases of models and workflows. Rather than treating the integration initiative as a one-time project, organizations can adopt a continuous improvement approach in which modeling, optimization, and operational practices evolve together. This may involve establishing a regular cadence of reviews in which stakeholders examine recent performance, discuss observed deviations between model recommendations and actual behavior, and agree on changes to features, parameters, or channel rules. In this way, organizational and governance structures become part of the broader system that supports the responsible and effective use of offline and call-center interactions within a Customer 360 framework for B2C sales optimization.

9 Conclusion

This paper has outlined a technical framework for incorporating offline and call-center interactions into digital personalization through an integrated Customer 360 approach for B2C sales optimization. The framework begins with a data architecture that aligns and harmonizes events from multiple channels at the customer level, enabling a coherent interaction history [50]. Offline visits and call-center contacts are mapped into canonical event types and summarized into features that can be integrated alongside digital traces, with attention to identity resolution, temporal alignment, and latency. This representation supports the construction of state variables that capture both observed attributes and latent propensities related to purchase, churn, and engagement.

On top of this data foundation, the paper has described mathematical models in which customer behavior is governed by an evolving state influenced by actions taken across digital, call-center, and offline channels. Response models map the state and actions to probabilities of purchase or other outcomes, while state transition models describe how interactions update latent propensities. These elements support the formulation of optimization problems for contact policies and channel allocation, ranging from static allocation rules based on expected value scores to dynamic policies that consider long-run reward through Markov decision process formulations [51]. Offline and call-center interactions enter these models not only as explanatory variables but also as actions and constraints that shape feasible policies.

Implementation aspects and empirical considerations have also been discussed, including the practical challenges of constructing reliable state features from heterogeneous data sources, evaluating the contribution of offline and call-center data to predictive performance and policy value, and maintaining model performance over time in the presence of drift. Sensitivity analysis with respect to data latency, feature definitions, and evaluation designs can help organizations understand which aspects of integration are most influential for outcomes. The approach emphasizes flexibility and neutrality, allowing firms to adapt model complexity, optimization horizons, and operational rules to their own environment while preserving a clear conceptual link between Customer 360 representation and personalization decisions.

Future work in applied contexts can build on this framework by exploring richer latent-state models, alternative optimization criteria that incorporate risk or fairness, and more extensive empirical evaluations that cover a variety of B2C sectors. As organizations continue to invest in omni-channel capabilities, the explicit integration of offline and call-center interactions into digital personalization may become a standard component of Customer 360 initiatives, providing a structured way to align sales and service decisions across channels without presupposing any specific technological implementation [52].

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