

# Customer Churn in the Age of Company Rating Sites and AI Technology: A Mixed Perspective on Trust Erosion and Retention Strategy

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## Abstract

Customer attrition remains one of the most pressing strategic concerns for firms operating in increasingly competitive, digitally mediated markets. While a substantial body of literature has examined predictive modelling techniques, win-back strategies, and the economic value of lost customers, comparatively little research has integrated contemporary consumer sentiment—particularly as expressed on public rating and discussion platforms—into this discourse. This paper synthesises established churn and customer-retention literature with a qualitative thematic analysis of anonymised consumer commentary drawn from a public online discussion forum addressing the question of what causes companies to lose customer trust. The analysis identifies six recurring themes: perceived exploitative pricing practices, unwanted or persistent marketing communication, corporate adoption of artificial intelligence at the expense of human service quality, ownership structure and leadership conduct, erosion of product or service quality, and failures of accountability and transparency. These findings are discussed in relation to existing churn-prediction and win-back frameworks, and implications for both theory and managerial practice are proposed. The paper concludes that predictive analytics alone are insufficient for retention strategy; firms must also attend to the qualitative, reputational dimensions of trust that increasingly circulate on public digital platforms.

**Keywords:** customer churn, customer retention, trust erosion, artificial intelligence, win-back strategy, netnography, e-commerce

## Introduction

Customer retention has long been recognised as more cost-effective than new customer acquisition, and this principle has only intensified in significance as digital markets have matured and switching costs for consumers have fallen. Businesses operating in the business-to-consumer (B2C) e-commerce space face particularly fierce competition, as rivals continuously seek to erode one another's client bases through aggressive market-penetration strategies (Shobana et al., 2023; Sucharitha et al., 2023). At the same time, the proliferation of company rating sites, review platforms, and social discussion forums has created a parallel, largely unmanaged channel through which consumers articulate—often in granular and emotionally candid terms—the precise behaviours that erode their trust in brands.

This paper argues that the extensive body of quantitative churn-prediction literature, while methodologically sophisticated, has generally not been triangulated with the qualitative, real-time sentiment expressed by consumers on public platforms. Understanding *why* trust erodes, in the customer's own words, offers a complementary lens to the statistical

modelling of *who* is likely to churn. Accordingly, this study pursues two aims: first, to synthesise the dominant strands of the churn, retention, and win-back literature; and second, to conduct a thematic analysis of anonymised consumer discourse on a public forum in order to identify the practical, lived triggers of trust erosion in the contemporary marketplace, with particular attention to the emerging role of artificial intelligence in customer-facing operations.

## Literature Review

### Predictive Modelling of Customer Churn

A dominant stream of churn research applies machine learning techniques to transactional and behavioural data in order to forecast attrition before it occurs. Shobana et al. (2023) and, in a closely related study, Sucharitha et al. (2023) both propose hybrid forecasting frameworks built on support vector machines, combined with the RFM (recency, frequency, monetary value) principle to segment lost customers into distinct categories for targeted win-back campaigns. These studies report measurable improvements in coverage ratio, hit ratio, lift, and precision when integrated forecasting models are applied, suggesting that firms which invest in granular behavioural data collection—covering search activity, purchase frequency, reviews, and feedback—are better positioned to intervene before defection occurs.

Complementary work has applied alternative algorithmic approaches to specific sectors. Yıldırım et al. (2023) compared LGBM, XGBoost, and Random Forest models using real transactional data from an automotive service provider, finding that ensemble tree-based methods offered strong predictive performance for identifying customers likely to lapse. In the telecommunications sector, Luo (2023) developed a decision-tree model and found that demographic variables such as age and marital status, alongside contract duration, were meaningful predictors of churn—longer-tenured contracts were associated with materially lower attrition risk. Jiang (2024) further emphasises that churn should not be treated as a monolithic outcome but rather as a spectrum of behaviours that data mining techniques can help to characterise, enabling firms to design more precisely targeted retention interventions.

Collectively, this stream of literature demonstrates that predictive analytics can meaningfully improve the efficiency of retention spend. However, these models are fundamentally correlational; they identify *who* is at risk without necessarily explaining the underlying relational or affective causes of defection—a gap partially addressed by the qualitative and conceptual literature reviewed below.

### The Economic Value of Lost and Reacquired Customers

A second strand of literature interrogates the financial logic underpinning retention and reacquisition decisions. Hogan et al. (2003) challenge the assumption, implicit in many traditional profitability models, that customers can be valued in isolation from one another. They demonstrate that the true cost of losing a customer depends on whether that customer defects to a competitor or abandons the product category entirely, and on the timing of that decision relative to the product life cycle; the loss of an early adopter is shown to be substantially more costly than the loss of a later adopter, owing to foregone social-influence effects such as word of mouth.

Building on the recognition that lost customers retain latent value, Kumar et al. (2015) provide the first empirical demonstration linking a customer's first-lifetime experience, their stated reason for defection, and the structure of a subsequent win-back offer to the probability of reacquisition, the duration of the second relationship, and its resulting profitability. Their findings indicate that customers with stronger first-lifetime relationships

are disproportionately more receptive to win-back offers, providing managers with a basis for prioritising reacquisition spend. Thomas et al. (2004) extend this logic to pricing strategy specifically, showing that an optimal reacquisition strategy typically combines a low initial win-back price with higher prices once the relationship has been re-established—a finding with direct implications for the design of retention offers.

### **Regain Management and Relationship Revival**

A related but conceptually distinct literature addresses the systematic management of lapsed-customer relationships as a discipline in its own right, rather than as an extension of standard retention practice. Stauß and Friege (1999) introduce the concept of "regain management," proposing a structured process of regain analysis, regain actions, and regain controlling, underpinned by a segmented database of lost customers. Homburg et al. (2007) provide empirical support for this conceptual framework, drawing on equity theory to show that a customer's perceived interactional, procedural, and distributive justice during a revival attempt strongly predicts revival-specific satisfaction, which in turn drives the success of the relationship revival itself; this effect is further moderated by customer characteristics such as variety-seeking tendency, involvement, and age.

Fisher (2001) situates this discussion within the UK retail banking sector, arguing that retention can no longer be understood merely as a function of customer satisfaction, but must instead account for competitive risk assessment—identifying which customers are vulnerable, in what numbers, and for what reasons—while simultaneously pursuing new customer acquisition from both traditional and direct-channel competitors.

### **Organisational and Relational Causes of Defection**

A number of studies move beyond transactional modelling to examine the relational and organisational dynamics that precede defection. Page et al. (1996) propose a six-stage graphical analysis process for understanding customer defection patterns and their implications for long-term profitability and growth, demonstrating the approach using data from a UK-based industrial equipment supplier. Grønhaug et al. (1999) offer a more cautionary account, documenting a case in which long-term buyer–seller relationships deteriorated gradually and largely undetected, because both sales representatives and management were constrained by rigid, experience-based mental models. Counterintuitively, they find that strong social ties between relational actors can impede rather than facilitate the flow of information necessary to detect relationship decline.

Coyles and Gokey (2005), drawing on a two-year study of 1,200 households across sixteen industries, argue that conventional churn metrics dramatically understate the true risk to firm revenue, since customers who quietly reduce or redirect their spending—without fully defecting—represent a substantially larger threat to profitability than outright attrition; their analysis suggests that this "share of wallet" erosion can carry up to ten times the financial impact of defection alone. Sahib et al. (2019), examining the telecommunications and mobile supply chain sector, similarly emphasise that customer loss imposes largely irrecoverable costs on firms and that competitive loss of customers frequently benefits rival organisations directly.

### **Small Business Retention and Broader Market Pressures**

Retention research has also been extended to the small business context, where survival pressures are especially acute. Hawkins and Hoon (2019) note that small businesses constitute the overwhelming majority of firms in the United States, yet are disproportionately affected by high failure rates linked to weak customer retention practices. Their study finds that relationship management and customer satisfaction function as foundational drivers of

revenue growth, brand equity, and long-term profitability, with even marginal improvements in retention rate translating into disproportionately large gains in financial performance—a pattern consistent with earlier findings cited in the retention literature more broadly. Carter (2008) situates these pressures within a wider environmental context, arguing that technological change, globalisation, more sophisticated and demanding consumers, and periodic market crises have collectively made customers more willing and able to switch providers, intensifying the strategic importance of retention relative to prior decades.

### **Synthesis and Identification of the Research Gap**

Taken together, the reviewed literature demonstrates considerable sophistication in predicting churn statistically (Shobana et al., 2023; Jiang, 2024; Luo, 2023; Sucharitha et al., 2023; Yıldırım et al., 2023) and in modelling the financial logic of reacquisition (Hogan et al., 2003; Kumar et al., 2015; Thomas et al., 2004). It also offers a conceptual foundation for the deliberate management of lapsed-customer relationships (Homburg et al., 2007; Stauß & Friege, 1999). However, this literature is overwhelmingly quantitative or conceptual in orientation, and none of the reviewed studies draw directly on the unprompted, naturally occurring commentary that consumers now generate on public rating and discussion platforms. Given that such platforms represent an increasingly influential arena in which trust is publicly negotiated, contested, and documented, this paper addresses that gap through a qualitative thematic analysis of anonymised forum discourse, presented in the following sections.

## **Methodology**

### **Research Design**

This study adopts a qualitative, exploratory research design employing netnography—the application of ethnographic methods to naturally occurring online communities and discourse (Kozinets, 2002)—to complement the predominantly quantitative orientation of the existing churn literature. Netnographic and qualitative content analysis approaches are well suited to identifying emergent, consumer-generated themes that structured surveys or transactional datasets are unlikely to surface, since they preserve the spontaneous, unprompted language in which consumers articulate trust and distrust.

### **Data Source and Sampling**

The data corpus consists of publicly accessible, unsolicited consumer commentary submitted in response to an open discussion prompt asking participants to identify the fastest way for a company to lose their trust. This design is analogous to a critical-incident or free-elicitation technique, in that it invites participants to nominate, in their own terms, the specific organisational behaviours they associate with trust erosion, rather than responding to a predetermined list of attributes. No personal identifiers, usernames, or platform-specific metadata are reported in this paper; all illustrative excerpts are presented as anonymised participant statements, consistent with ethical conventions for the secondary analysis of publicly available social media data (British Psychological Society, 2021; Franzke et al., 2020).

### **Analytical Approach**

Data were analysed using an inductive thematic analysis procedure following the six-phase framework of Braun and Clarke (2006): familiarisation with the data; generation of initial codes; identification of candidate themes; review of themes against the coded extracts; definition and naming of themes; and production of the final analytic narrative. Coding was

conducted at the level of the individual comment, with related codes subsequently clustered into higher-order themes. Given the exploratory nature of the study and the relatively bounded size of the discussion thread analysed, the findings are presented as illustrative and hypothesis-generating rather than statistically generalisable, consistent with standard conventions for small-sample qualitative research.

### **Ethical Considerations**

As the data analysed were drawn from a publicly accessible forum without direct researcher interaction with participants, and as all excerpts have been anonymised and stripped of identifying detail prior to inclusion in this paper, the study is considered to pose minimal risk in accordance with prevailing guidance on the ethical use of publicly available online data (Franzke et al., 2020). No attempt was made to identify, contact, or re-identify individual contributors.

## **Results and Discussion**

Thematic analysis of the discussion corpus yielded six interrelated themes, summarised below with anonymised illustrative extracts.

### **Theme One: Perceived Exploitative Pricing Practices**

The most salient theme concerned pricing behaviour perceived as exploitative or deceptive, most frequently described through the lens of "shrinkflation"—simultaneous price increases and quality or quantity reductions—and unannounced subscription renewal at higher rates. One participant described losing trust in any brand that raises prices while reducing product features, only to market the change as an improvement. Another respondent specifically identified automatic renewal at a higher price without prior notice as damaging, explaining that the financial cost mattered less than the implicit assumption that the change would go unnoticed, which was interpreted as a signal of how little the firm valued the relationship. This theme aligns closely with the profitability and reacquisition-pricing literature reviewed above (Thomas et al., 2004), suggesting that pricing transparency functions not merely as a transactional variable but as a signal of relational respect.

### **Theme Two: Unwanted and Persistent Marketing Communication**

A second prominent theme concerned communication practices perceived as intrusive or disrespectful of stated preferences. Participants frequently cited continued marketing emails or telephone solicitation after having explicitly opted out, with one respondent describing a shift away from a major hospitality brand specifically due to repeated unwanted calls. Related complaints referenced aggressive in-person sales tactics at trade events, including badge scanning and prolonged pitches delivered without the prospective customer's consent. This theme resonates with the relational-fatigue dynamics described by Grønhaug et al. (1999), in that repeated disregard for a customer's expressed boundaries appears to accelerate relational deterioration independent of product quality.

### **Theme Three: Corporate Adoption of Artificial Intelligence**

A theme of particular relevance to the contemporary marketplace centred on the visible or perceived use of artificial intelligence in customer-facing functions, including AI-generated marketing imagery, AI-powered chatbots, and workforce reductions attributed to AI adoption. Several participants expressed that visibly low-effort AI-generated content signalled a broader willingness by the firm to cut corners, even when they held no general objection to AI as a technology. Others linked AI adoption directly to layoffs, framing

workforce displacement in favour of automation as a marker of declining organisational trustworthiness. This theme did not have a direct precedent in the reviewed churn literature, which has generally treated AI as a tool of analysis (e.g., churn prediction) rather than as a customer-facing signal that itself shapes trust—representing a notable extension of the existing literature.

#### **Theme Four: Ownership Structure, Leadership Conduct, and Political Positioning**

A fourth theme concerned the perceived influence of ownership structure and leadership conduct on brand trust. Several participants associated private equity ownership or public listing with a gradual erosion of an organisation's founding values in favour of short-term profit. Others linked distrust directly to the public conduct, statements, or political positioning of company leadership. This theme intersects with, but extends beyond, the profitability-focused literature reviewed in Section 2.2, suggesting that governance and leadership visibility—factors largely absent from transactional churn models—may constitute an independent driver of relational risk.

#### **Theme Five: Decline in Product or Service Quality**

A recurring and comparatively conventional theme concerned direct decline in product or service quality, particularly when accompanied by a perceived unwillingness on the part of the firm to acknowledge the decline. Several participants described losing trust specifically when quality deterioration was met with denial or deflection rather than acknowledgement. This theme is broadly consistent with the traditional determinants of customer satisfaction identified in the retention literature (Hawkins & Hoon, 2019) but highlights that the *organisational response* to quality decline—rather than the decline itself—may be the more decisive trust-eroding factor.

#### **Theme Six: Failures of Accountability and Transparency**

A final, closely related theme concerned failures of accountability, including refusal to take responsibility for errors, lack of follow-up after complaints, and reliance on technicalities to avoid resolving disputes. One participant described a contracting dispute involving a substantially inflated post-acceptance estimate as a clear example of bad-faith conduct. Others emphasised that a lack of follow-through on stated commitments to "look into" a complaint was itself sufficient to end the relationship, independent of the original issue. This theme most directly parallels the justice-based framework proposed by Homburg et al. (2007), in that perceived procedural and interactional injustice—rather than the underlying service failure—appears central to the erosion of trust.

The thematic findings both corroborate and extend the reviewed literature. Consistent with Homburg et al. (2007) and Stauß and Friege (1999), the data suggest that *how* a firm responds to failure—through acknowledgement, procedural fairness, and follow-through—is at least as consequential for trust as the failure itself. Similarly, the pricing-related theme lends qualitative support to the reacquisition-pricing logic proposed by Thomas et al. (2004), while adding nuance: participants did not object to price increases per se, but to the perceived concealment or misrepresentation of such increases.

The most theoretically significant extension concerns the emergent role of artificial intelligence as a *bidirectional* force in the churn ecosystem. Existing literature treats AI predominantly as an analytical instrument used by firms to forecast and pre-empt churn (Shobana et al., 2023; Jiang, 2024; Sucharitha et al., 2023; Yıldırım et al., 2023). The present findings suggest that AI simultaneously functions as a *visible signal* to consumers, capable of independently triggering the very attrition that predictive models are designed to forecast. This suggests a reflexive relationship: firms increasingly deploy AI to predict and prevent

churn, while the visible deployment of AI in customer-facing contexts may itself generate the distrust that produces churn. Future predictive models may therefore benefit from incorporating sentiment toward a firm's AI-driven customer experience as an explanatory variable in its own right, rather than treating AI solely as a backend analytical tool.

The ownership-and-leadership theme further suggests that governance-level variables—private equity ownership, public listing, and executive conduct—may warrant closer integration into churn and retention frameworks, which have historically concentrated on transactional and service-level predictors (Hogan et al., 2003; Kumar et al., 2015).

### **Managerial Implications**

Several practical implications follow from this synthesis. First, firms should prioritise transparent communication of price and policy changes, given the apparent sensitivity of consumers to perceived concealment rather than the change itself. Second, marketing and communication functions should rigorously respect stated consumer preferences regarding contact frequency and channel, as violations of these preferences appear to carry disproportionate reputational cost. Third, organisations deploying AI in customer-facing roles should carefully evaluate the visible quality and framing of such deployments, since poorly executed or opaque AI implementation may independently damage trust irrespective of underlying service quality. Fourth, complaint-handling processes should be evaluated not only for resolution speed but for perceived procedural and interactional fairness, consistent with the equity-theory findings of Homburg et al. (2007). Finally, firms should recognise that governance and leadership conduct are increasingly visible and consequential to consumer trust, suggesting that reputational risk management should extend beyond customer service functions to encompass corporate governance communication more broadly.

### **Limitations and Future Research**

This study is subject to several limitations. The qualitative corpus, while rich, is drawn from a single public discussion thread and cannot be assumed to be representative of the broader consumer population; self-selection into online discussion forums may over-represent particularly dissatisfied or vocal consumers. Additionally, because the data are anonymised and platform metadata were not analysed, no demographic or sector-specific segmentation of the findings was possible. Future research should seek to validate the six identified themes, particularly the AI-as-trust-signal theme, using larger, more representative datasets and, where possible, integrate them into quantitative churn-prediction models as additional predictive features. Longitudinal designs tracking sentiment toward specific firms' AI deployments alongside subsequent churn behaviour would be particularly valuable in establishing the directionality and strength of the relationship proposed in Section 5.

## **Conclusion**

This paper has synthesised the established quantitative and conceptual literature on customer churn, lost-customer valuation, and win-back strategy, and has complemented this synthesis with a qualitative thematic analysis of anonymised, naturally occurring consumer discourse. The findings suggest that while predictive analytics remain indispensable for identifying at-risk customers, they do not fully capture the qualitative, reputational triggers of trust erosion increasingly visible on public rating and discussion platforms—particularly those relating to the visible deployment of artificial intelligence. Firms seeking to reduce churn in the contemporary marketplace should therefore integrate qualitative social listening alongside quantitative predictive modelling, and should treat transparency, procedural

fairness, and the visible quality of AI implementation as first-order strategic considerations rather than peripheral concerns.

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