

ORIGINAL RESEARCH

Open access

Digital Customer Exit Management: A Conceptual Framework for Understanding Churn Signals, Switching Intentions, and Retention Interventions

Amal Al-Balushi^{1*}, Saif Al-Hinai¹

Abstract

In digital markets, customer exit has become faster, quieter, and more difficult to reverse. Customers can reduce usage, compare alternatives, migrate to competitors, or cancel subscriptions with minimal friction. Despite this reality, many firms still allocate disproportionate managerial attention to acquisition rather than structured exit management. Existing research offers important insights into customer churn prediction, switching behaviour, engagement, loyalty programmes, service recovery, and win-back campaigns. However, these streams are often treated as separate domains rather than as connected stages in a customer exit process. This fragmentation limits managers' ability to detect early churn signals, interpret switching intentions, and deploy retention interventions at the right time. This article proposes the Digital Customer Exit Management Framework as an original conceptual framework for digital customer retention. The framework links observable churn signals, psychological and contextual switching intentions, and targeted retention interventions into a unified process model. It positions customer exit not as a single cancellation event but as a dynamic trajectory that can be anticipated, interpreted, and influenced. The article argues that proactive exit management is a strategic capability for digital businesses. By moving from reactive retention to early signal detection and intervention alignment, firms can reduce avoidable churn, protect customer lifetime value, and improve the quality of customer relationship management. The framework provides a structured roadmap for managers and a foundation for future empirical testing.

Keywords Conceptual framework, Digital customer exit, Churn signals, Switching intentions, Retention interventions, Customer churn

*Correspondence:

Amal Al-Balushi
amal.balushi@squ.edu.om

¹ Department of Digital Business and Innovation, Faculty of Economics, Sultan Qaboos University, Muscat, Oman

Introduction

Digital businesses increasingly compete in markets where customer relationships are data-rich but fragile. Subscription platforms, e-commerce firms, digital services, and online marketplaces can track engagement continuously, yet customers can also leave with little warning or explanation. Prior retention research shows that churn management requires more than identifying high-risk customers, because some retention actions may be ineffective or even misdirected when firms misunderstand the customer's exit trajectory [1, 2].

The central problem is that firms often treat customer exit as a late-stage cancellation event rather than as an unfolding process. Ascarza, Netzer, and Hardie demonstrate that some customers disengage silently before leaving, which means exit may be preceded by subtle behavioural changes rather than explicit complaints [3]. Predictive churn research

similarly shows that customer defection can be anticipated through behavioural, transactional, and textual data, but these signals must be interpreted within a broader managerial process rather than used only as statistical scores [4, 5].

The literature on engagement and experience further suggests that exit risk emerges when customers no longer perceive sufficient value, emotional connection, or relational benefit from continued participation. Customer engagement research explains that interaction intensity, affective connection, and behavioural participation influence relationship strength [6, 7]. Customer experience management research also shows that firms must manage interactions across journeys, touchpoints, and data environments rather than relying on isolated service encounters [8-10].

This article addresses the lack of an integrated, process-based conceptual framework connecting early churn signals, switching intentions, and retention interventions. The aim is to construct the Digital Customer Exit Management Framework, which conceptualises exit as a staged managerial challenge moving from signal detection to switching-risk interpretation and intervention selection. This contribution responds to calls for more strategic retention management and more precise customer relationship management in data-rich environments [1, 11].

Digital Customer Exit as a Management Challenge

Digital customer exit differs from traditional customer defection because it can occur rapidly, invisibly, and across multiple channels. In traditional service contexts, exit may be preceded by face-to-face complaints, contract renewal discussions, or visible reductions in purchase frequency. In digital environments, however, reduced usage, lower engagement, declining response to campaigns, and competitor exploration may develop before any explicit cancellation request appears, making early detection central to retention management [3, 8].

The managerial challenge is intensified by low switching costs and constant competitive visibility. Customers can compare prices, features, reviews, social proof, and promotional offers almost instantly, which means perceived value deterioration may quickly translate into switching intention. Research on customer experience and engagement suggests that firms must maintain relevance, trust, and interaction value continuously because weak experiences can erode relational commitment before managers recognise the problem [9, 12].

Digital customer exit is also a data interpretation challenge. Churn prediction studies show that behavioural and transactional data can support early warning systems, but the managerial meaning of a signal depends on context, timing, and customer value [4, 13]. A missed payment, reduced usage, or negative support interaction may indicate temporary friction, dissatisfaction, economic constraint, or active migration to a competitor, so firms need a framework that links signals to probable exit mechanisms.

Another challenge is that retention spending can be wasteful when interventions are not matched to the customer's actual exit stage. Ascarza's work on retention futility warns that targeting high-risk customers does not automatically improve outcomes when customers are already committed to leaving or when interventions fail to address the underlying cause [2]. A digital exit management approach must therefore distinguish between early disengagement, emerging switching intention, active competitor movement, cancellation, and possible win-back opportunities.

Churn Signals and Behavioral Indicators

Churn signals are observable behavioural, transactional, relational, and communicative indicators that precede customer exit. In digital environments, these signals include declining login frequency, reduced feature use, shorter sessions, fewer transactions, lower response to marketing communication, and increased support contact. Churn prediction studies demonstrate that these data traces can be modelled to estimate defection probability, especially when firms combine structured behavioural data with customer history and engagement patterns [4, 13, 14].

A second category of churn signals comes from customer language and sentiment. Textual data from support tickets, complaints, chat messages, reviews, and service interactions can reveal dissatisfaction before customers cancel. De Caigny, Coussement, De Bock, and Lessmann show that textual information can improve churn prediction when incorporated into modelling architectures, indicating that customer exit is not only behavioural but also communicative [5].

A third category concerns financial and transactional instability. Payment failures, delayed renewals, downgrade behaviour, unused credits, basket abandonment, declining order value, and reduced subscription intensity may signal weakening commitment. Profit-driven churn modelling highlights that firms should not only predict who will leave but also evaluate the economic value of intervention, because not every churn signal justifies the same retention response [11, 15].

The proposed framework treats churn signals as staged indicators rather than isolated metrics, because signal intensity changes as customers move from mild disengagement to active exit preparation. Table 1 classifies the digital churn signals and behavioural indicators that predict customer exit. This classification draws on churn prediction, customer engagement, and customer experience research to show how behavioural data, sentiment data, transactional data, and relationship data can be converted into managerial early-warning categories [1, 4, 6, 8].

Table 1. Digital Churn Signals and Behavioural Indicators: Categories, Data Sources, and Predictive Strength

Churn signal category	Observable behavioural indicators	Typical digital data sources	Predictive strength	Managerial interpretation	Recommended monitoring frequency
Usage decline	Reduced login frequency, shorter sessions, lower feature use, fewer interactions	App analytics, web analytics, platform activity logs, product telemetry	High when sustained over repeated periods	Customer is reducing reliance on the service and may be testing alternatives	Daily or weekly, depending on service cycle
Engagement weakening	Lower email opens, fewer clicks, reduced content interaction, declining campaign response	CRM systems, marketing automation platforms, email analytics, push-notification data	Moderate to high when combined with usage decline	Customer attention and relational involvement are weakening	Weekly
Transaction reduction	Lower purchase frequency, smaller order value, fewer renewals, subscription downgrades	Billing systems, e-commerce transaction logs, subscription management systems	High when linked to prior high-value behaviour	Customer value extraction is declining and exit risk is rising	Weekly or monthly
Support dissatisfaction	More complaints, repeated tickets, unresolved issues, negative sentiment, refund requests	Helpdesk records, chat transcripts, call logs, complaint databases	High when sentiment is negative and issue recurrence is frequent	Customer is experiencing unresolved friction that may become switching motivation	Real time or daily
Payment instability	Failed payments, delayed invoices,	Payment gateways, billing	Moderate, unless	Exit may reflect financial friction,	Real time

	card expiry, renewal friction, rejected transactions	systems, subscription renewal records	combined with reduced usage or complaints	passive cancellation, or declining commitment	
Product substitution behaviour	Reduced use of core features, increased use of export tools, fewer integrations, account inactivity after data download	Product analytics, account settings, API logs, data export records	High in platform and SaaS contexts	Customer may be preparing to migrate data or workflows elsewhere	Real time or weekly
Community disengagement	Fewer reviews, reduced forum participation, lower referral activity, declining social interaction	Online communities, review systems, referral platforms, social listening tools	Moderate	Customer is withdrawing from relational and social elements of the brand	Monthly
Loyalty programme inactivity	Unused rewards, lower points redemption, reduced tier progression, declining participation	Loyalty platforms, reward dashboards, CRM records	Moderate to high among loyalty-active customers	Customer no longer values relational incentives or programme benefits	Monthly
Negative communication signals	Complaint language, cancellation questions, competitor mentions, price concerns, dissatisfaction narratives	Chat logs, support tickets, surveys, review text, social media messages	High when combined with behavioural decline	Customer is expressing exit-related cognition before formal cancellation	Real time or daily
Silent disengagement	No complaint but steady decline in use, transactions, and campaign response	Integrated CRM, product analytics, transaction data, marketing data	High when detected early	Customer may leave without explicit warning, requiring proactive diagnosis	Weekly

Switching Intentions and Competitor Movement

Switching intention represents the customer's psychological readiness to move from the current provider to an alternative. In digital markets, this readiness may develop before formal cancellation and may be shaped by dissatisfaction, perceived value decline, weakened trust, or better competitor offers. Research on customer experience management shows that customers evaluate relationships across cumulative touchpoints, meaning that switching intention can emerge from repeated small frictions rather than a single failure [10].

Competitor movement becomes especially important when customers can compare alternatives quickly and cheaply. Platform users, subscription customers, and e-commerce buyers may encounter competitor promotions, social recommendations, price comparisons, or feature comparisons while still being technically active with the current firm.

Studies of switching intention in digital and service contexts show that trust, satisfaction, perceived usefulness, and alternative attractiveness influence whether customers remain, switch, or continue searching [16, 17].

Switching intention is also affected by engagement decay. When customers stop participating in relational activities, ignore communications, or reduce emotional connection with the brand, they become more receptive to external offers. Engagement research suggests that customer participation, relational investment, and perceived value co-creation strengthen retention, while weakened engagement may create psychological openness to exit [18-20].

The proposed framework treats competitor movement as both a market signal and a customer-level behavioural signal. Customer comeback and repeat churn research shows that departure is not always final, because customers may return, leave again, or continue comparing alternatives after reactivation [21, 22]. **Table 2** summarises the drivers of switching intentions and the role of competitor activity.

Table 2. Switching Intentions and Competitor Movement: Psychological Drivers, Situational Triggers, and Competitive Dynamics

Switching driver	Psychological mechanism	Situational trigger	Competitor dynamic	Observable digital indicator	Managerial implication
Perceived value decline	Customer believes benefits no longer justify cost, time, or attention	Price increase, reduced usage, feature fatigue, weaker service relevance	Competitors appear to offer better value or clearer benefits	Reduced usage, downgrade behaviour, price-page visits, comparison searches	Reframe value proposition and personalise benefit communication
Dissatisfaction accumulation	Repeated small failures create frustration and lower tolerance	Unresolved tickets, repeated errors, poor service recovery, delayed support	Competitors gain appeal as lower-friction alternatives	Complaint repetition, negative sentiment, cancellation-related support questions	Prioritise service recovery before financial incentives
Trust weakening	Customer doubts provider reliability, fairness, or competence	Data errors, billing confusion, poor communication, perceived opacity	Competitors may present themselves as safer or more transparent	Support escalation, lower engagement, privacy concern messages	Use transparent explanations and visible corrective action
Social influence	Customer is influenced by peer reviews, community narratives, or recommendations	Negative reviews, influencer comparisons, peer migration, social proof	Competitor legitimacy increases through network visibility	Referral decline, social listening signals, review monitoring	Monitor social sentiment and respond with evidence-based reassurance
Alternative attractiveness	Customer perceives another provider as superior in price, features, convenience, or identity fit	Promotions, free trials, bundled offers, platform recommendations	Competitors reduce perceived switching risk	Competitor mentions in tickets, search behaviour, trial-related language	Match intervention to the specific attraction point

Switching cost reduction	Customer believes moving is easy and low-risk	Data portability, simple cancellation, automated onboarding elsewhere	Competitors remove migration barriers	Data export, integration removal, account-setting changes	Reinforce embedded value and simplify continuation
Service failure shock	A major incident accelerates exit consideration	Outage, data breach, failed delivery, major billing error	Competitors become immediate substitutes	Spike in complaints, refund requests, negative reviews	Deploy rapid service recovery and compensation
Identity or preference mismatch	Customer feels the service no longer fits needs, lifestyle, business model, or goals	Changing customer needs, new use case, demographic shift, business growth	Niche competitors appear more relevant	Feature abandonment, changed search terms, support requests about limitations	Offer segmentation-based pathways or product migration options
Competitive promotion exposure	Customer receives direct incentive to leave	Discount campaign, referral bonus, bundled competitor offer	Competitors actively target vulnerable users	Competitor names in communication, reduced campaign response, price objections	Use selective counteroffers only when economically justified
Post-exit comparison	Customer continues evaluating whether leaving was beneficial	Trial of competitor, temporary return, failed migration, regret	Competitor performance determines win-back possibility	Account reactivation, abandoned cancellation, renewed browsing	Design win-back campaigns based on exit reason and timing

Retention Interventions

Retention interventions must be designed as a portfolio rather than a single generic campaign. Some customers require reassurance, some need service recovery, some respond to loyalty incentives, and others need a redesigned value proposition. Research on loyalty programmes shows that rewards, targeted coupons, and programme design can influence retention, but effectiveness depends on fit with customer motivation and relationship stage [23-25].

Proactive interventions are most useful when churn signals are early and switching intention is still weak or uncertain. These interventions include personalised education, usage prompts, benefit reminders, onboarding support, and low-friction problem diagnosis. Customer engagement strategy research suggests that firms should strengthen interaction value before the customer becomes fully committed to exit [19].

Reactive interventions become necessary when dissatisfaction is explicit or switching intention is stronger. Service recovery, compensation, transparent explanation, and human support are especially important when customers experience failure, unfairness, or trust erosion. Customer relationship management campaign research also indicates that interventions may influence not only targeted customers but also wider social or network effects, which makes tone, timing, and fairness important [26].

Win-back interventions apply after cancellation, dormancy, or competitor trial. Research on returning customers and repeat churn shows that some former customers can be economically valuable, but they may also be more likely to leave

again if the original exit reason remains unresolved [22, 23]. **Table 3** maps retention interventions to churn signal stages and switching intention levels.

Table 3. Retention Interventions for Digital Customer Exit: Proactive Offers, Service Recovery, and Win-Back Campaigns Aligned with Churn Risk

Churn stage	Signal intensity	Switching intention level	Suitable intervention type	Example intervention	Timing logic	Success metric
Early disengagement	Low to moderate	Weak or unclear	Proactive engagement support	Usage reminders, feature education, onboarding nudges, personalised tutorials	Intervene before dissatisfaction becomes explicit	Recovered usage frequency and renewed engagement
Value uncertainty	Moderate	Emerging	Value reinforcement	Personalised benefit summary, plan optimisation, relevant feature recommendation	Intervene when customer still evaluates whether the service is worthwhile	Increased feature use, reduced downgrade behaviour
Support friction	Moderate to high	Emerging to strong	Service recovery	Priority support, issue resolution, apology, explanation, follow-up confirmation	Intervene immediately after unresolved service problems	Ticket resolution, sentiment improvement, complaint reduction
Price concern	Moderate	Emerging	Selective economic intervention	Temporary discount, plan migration, loyalty credit, bundled value offer	Intervene when price is the stated barrier and customer value justifies incentive	Renewal, margin-adjusted retention, reduced downgrade
Trust erosion	High	Strong	Transparency and reassurance	Clear explanation, governance disclosure, corrective action, human escalation	Intervene before cancellation when trust can still be rebuilt	Trust recovery, reduced cancellation requests
Competitor attraction	High	Strong	Counter-positioning	Feature comparison, migration support reversal, targeted offer, value evidence	Intervene when competitor appeal is visible but customer has not fully exited	Reduced competitor-related support signals
Passive cancellation risk	Moderate to high	Variable	Friction removal	Payment update support, renewal reminder, account recovery, billing clarification	Intervene before unintended churn becomes formal churn	Payment recovery and successful renewal

Active cancellation	High	Very strong	Save intervention	Cancellation survey, tailored save offer, human support, alternative plan	Intervene during cancellation flow without creating coercive friction	Save rate and customer satisfaction after save
Dormancy after exit	Medium	Unclear	Win-back learning	Exit reason analysis, personalised reactivation message, changed-offer communication	Intervene after enough time has passed for reconsideration	Reactivation and second-period retention
Repeat churn risk	High after return	Strong if unresolved	Post-win-back stabilisation	Dedicated onboarding, issue monitoring, loyalty reinforcement, proactive support	Intervene immediately after return to prevent repeated exit	Sustained retention and lower repeat churn

Proposed Digital Customer Exit Management Framework

The Digital Customer Exit Management Framework conceptualises customer exit as a dynamic process rather than a discrete cancellation event. The framework begins with signal detection, where firms identify behavioural, transactional, communicative, and engagement-based indicators of possible defection. Predictive churn studies demonstrate the value of combining behavioural traces, structured customer records, and advanced modelling techniques to identify customers at risk before exit occurs [27-30].

The second stage is switching risk assessment, where firms interpret whether churn signals reflect temporary inactivity, dissatisfaction, value deterioration, competitor attraction, or active migration. This stage requires more than algorithmic scoring because a high churn probability does not automatically indicate the right intervention. Fairness-aware and profit-driven churn research suggests that managers must consider customer value, intervention cost, model bias, and treatment appropriateness when deciding whether and how to act [11, 30].

The third stage is intervention selection, where firms align retention responses with the customer's exit stage and underlying motivation. Loyalty research supports the use of targeted rewards and coupons, but these tools should not substitute for service recovery when the real cause is unresolved dissatisfaction [23, 24]. Customer experience and engagement research further suggests that interventions should restore relevance, trust, convenience, or relational value depending on the specific exit mechanism [8, 18].

The fourth stage is outcome evaluation, where firms assess whether the intervention prevented churn, delayed churn, improved satisfaction, generated profitable retention, or merely subsidised customers who would have stayed anyway. The framework therefore includes feedback loops from outcomes back to signal detection, model refinement, and intervention playbooks. **Table 4** presents the proposed Digital Customer Exit Management Framework integrating signals, intentions, and interventions.

Table 4. Digital Customer Exit Management Framework: Components, Decision Logic, and Feedback Loops for Reducing Churn

Framework component	Core question	Key input	Managerial decision logic	Main output	Feedback loop

Signal detection	What evidence suggests that the customer may be moving toward exit?	Usage data, engagement data, transaction data, support text, payment records	Detect early, repeated, and multi-source indicators rather than relying on cancellation events	Churn signal profile	Update signal thresholds based on later outcomes
Signal classification	What type of churn signal is present?	Behavioural decline, sentiment decline, financial instability, product substitution, silent disengagement	Separate temporary inactivity from meaningful exit preparation	Signal category and intensity level	Refine categories using intervention response data
Switching risk assessment	Is the customer psychologically or behaviourally preparing to switch?	Complaints, competitor mentions, price concerns, data export, reduced engagement	Interpret whether risk reflects dissatisfaction, competitor attraction, value decline, or passive churn	Switching risk diagnosis	Improve switching models using cancellation and win-back evidence
Customer value assessment	Is intervention economically and strategically justified?	Lifetime value, margin, acquisition cost, referral value, strategic segment	Avoid wasteful intervention where retention is unlikely or unprofitable	Intervention priority tier	Recalibrate value thresholds after retention ROI analysis
Intervention selection	What retention action best matches the exit mechanism?	Signal category, risk level, customer value, relationship history	Match proactive support, economic offer, service recovery, reassurance, or win-back to the cause	Intervention playbook	Compare effectiveness across customer segments
Channel selection	Where should the intervention occur?	Preferred channel, urgency, customer history, service context	Use low-friction digital channels for mild risk and human escalation for high-risk or emotional cases	Contact channel and timing	Learn which channels work for each risk type
Outcome evaluation	Did the intervention change the customer trajectory?	Renewal, continued usage, satisfaction, complaint resolution, reactivation, profitability	Distinguish saved customers from delayed churn or subsidised retention	Retention outcome classification	Feed results into modelling and playbook redesign
Governance control	Was the intervention fair, compliant, and strategically consistent?	Privacy rules, fairness checks, consent status, incentive policy, brand standards	Prevent discriminatory, intrusive, or margin-eroding retention practices	Governed exit management process	Audit interventions and revise governance rules
Learning system	What should the firm learn from exits and saves?	Exit reasons, intervention outcomes, churn	Treat exit as a source of strategic	Improved retention	Strengthen future signal detection

		model errors, customer feedback	learning rather than only a loss event	knowledge base	and intervention design
Strategic review	How does exit management affect customer lifetime value and market position?	Churn rate, retention ROI, win-back value, competitor movement, segment trends	Connect operational retention actions to strategic customer asset management	Exit management performance dashboard	Adjust acquisition, retention, and product strategy

Figure 1 presents the Digital Customer Exit Management Framework as a staged process linking churn signals, switching intentions, retention interventions, and outcome learning.

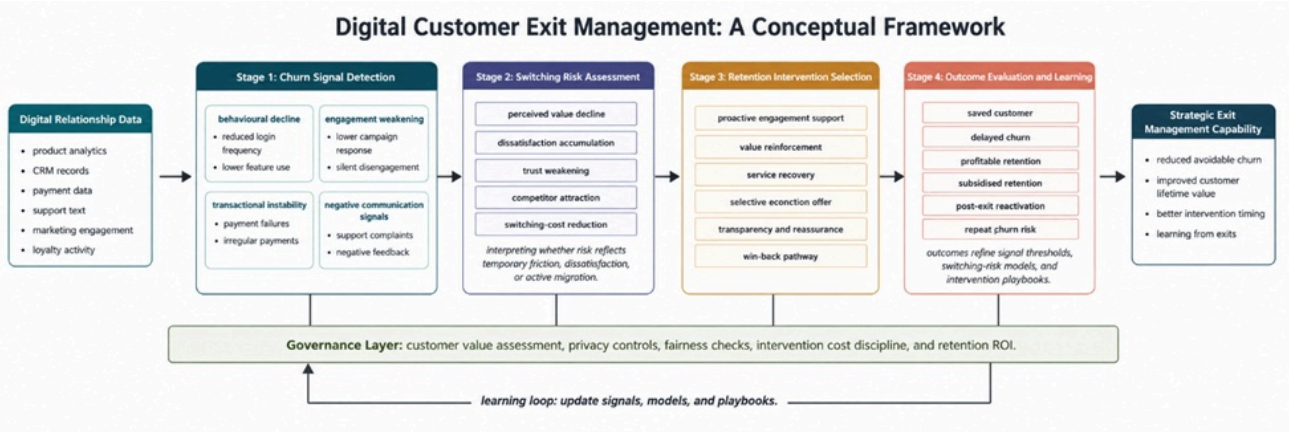


Figure 1. Digital Customer Exit Management Framework: From Churn Signal Detection to Switching Risk Assessment, Retention Intervention, and Outcome Learning

Managerial Implementation Pathway

The first managerial step is to build a churn signal dashboard that integrates product usage, CRM data, payment records, support interactions, marketing engagement, and customer value indicators. Such a dashboard should not merely rank customers by churn probability; it should classify the type of signal and indicate the probable exit mechanism. Hybrid churn models and textual churn prediction research show that combining structured and unstructured data can improve detection and interpretation [4, 5].

The second step is to establish a cross-functional exit management team. Customer exit is not owned only by marketing, because product design, pricing, customer service, billing, data analytics, and customer success all shape the exit trajectory. Strategic customer experience research supports this cross-functional view by showing that customer experience management requires coordinated implementation across organisational units and touchpoints [8-10].

Figure 2 outlines the managerial implementation pathway for building a proactive digital customer exit management capability.

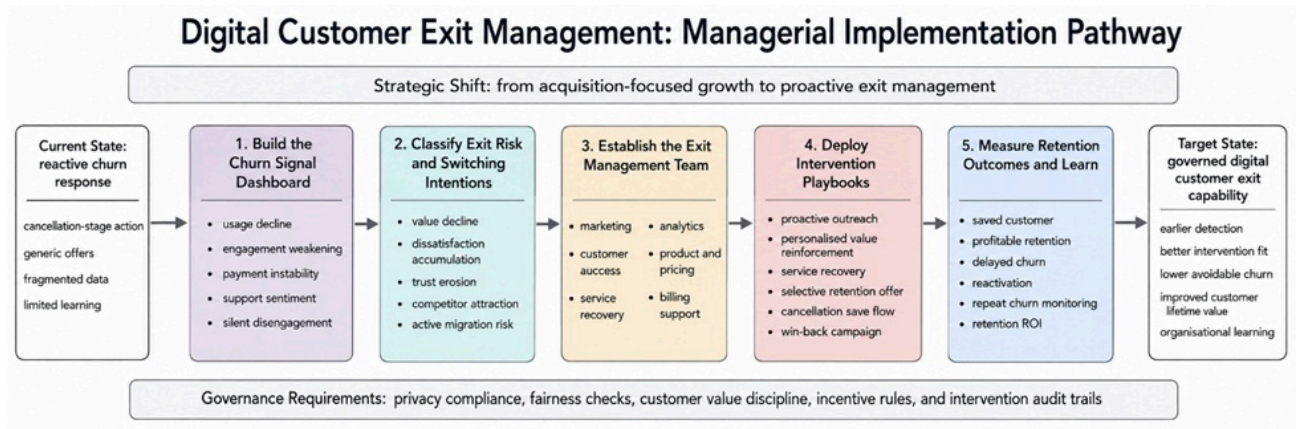


Figure 2. Managerial Implementation Pathway for Digital Customer Exit Management: Building Dashboards, Teams, Playbooks, Governance, and Retention Learning

The third step is to design intervention playbooks and retention ROI measures. Managers should define which interventions are appropriate for early disengagement, service failure, price concern, competitor movement, active cancellation, and post-exit win-back. Profit-driven churn management and loyalty programme research indicate that retention should be evaluated through economic contribution, customer lifetime value, and long-term relationship quality rather than simple save-rate metrics [11, 23, 25].

Limitations

The first limitation is that the proposed Digital Customer Exit Management Framework is conceptual and has not yet been empirically tested as a unified model. Although its components are grounded in prior research on churn prediction, engagement, experience, loyalty, switching, and win-back behaviour, the framework itself requires validation across industries and customer segments. Future studies could test whether the staged integration of signal detection, switching-risk assessment, intervention selection, and outcome evaluation improves retention performance beyond conventional churn scoring [1, 27, 28].

The second limitation concerns industry variation. Digital customer exit may differ across subscription media, software-as-a-service, telecommunications, e-commerce, financial services, and digital platforms because usage cycles, contract structures, switching costs, and competitor visibility vary substantially. For example, churn prediction in browser, broadcast, telecommunications, and business-to-business contexts may rely on different signals and require different modelling assumptions [14, 27, 28, 30].

The third limitation concerns data privacy, fairness, and customer trust. Digital exit management relies on behavioural monitoring, textual analysis, intervention targeting, and predictive scoring, all of which may raise ethical concerns if customers perceive retention actions as intrusive, manipulative, or unfair. Fairness-aware churn modelling and customer experience research suggest that firms must govern data use carefully so that proactive retention strengthens rather than damages customer trust [9, 12, 30].

Conclusion

This article proposed the Digital Customer Exit Management Framework as a conceptual model for understanding and managing customer departure in digital environments. The framework integrates churn signals, switching intentions, and retention interventions into a staged process that begins before cancellation and continues through win-back learning. It reframes churn as a manageable trajectory rather than a sudden endpoint.

The framework contributes to digital marketing and customer retention by showing how firms can move from acquisition-dominant thinking toward systematic exit management. It argues that reduced usage, weakened engagement, negative sentiment, payment instability, and competitor movement should be interpreted together rather than handled as disconnected warning signs. It also emphasises that retention interventions must be matched to the customer's exit stage, motivation, and value.

For managers, the central implication is that exit management should become a strategic capability supported by data, governance, cross-functional coordination, and continuous learning. For researchers, the framework provides a basis for empirical testing, industry comparison, and further development of customer exit theory in digital markets. Customer churn is not only a loss to be counted after it happens; it is a process that can be anticipated, influenced, and learned from.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 10 May 2026

Revised: 20 Jun 2026

Accepted: 01 Aug 2026

Published online: 18 September 2026

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at <https://creativecommons.org/licenses/by-nc-sa/4.0/>.

References

- Ascarza E, Neslin SA, Netzer O, Anderson Z, Fader PS, Gupta S, et al. In pursuit of enhanced customer retention management: Review, key issues, and future directions. *Cust Needs Solut.* 2018;5(1):65-81.
- Ascarza E. Retention futility: Targeting high-risk customers might be ineffective. *J Mark Res.* 2018;55(1):80-98.

Ascarza E, Netzer O, Hardie BG. Some customers would rather leave without saying goodbye. *Mark Sci.* 2018;37(1):54-77.

De Caigny A, Coussement K, De Bock KW. A new hybrid classification algorithm for customer churn prediction based on logistic regression and decision trees. *Eur j Oper Res.* 2018;269(2):760-72.

De Caigny A, Coussement K, De Bock KW, Lessmann S. Incorporating textual information in customer churn prediction models based on a convolutional neural network. *Int J Forecast.* 2020;36(4):1563-78.

Pansari A, Kumar V. Customer engagement: the construct, antecedents, and consequences. *J Acad Mark Sci.* 2017;45(3):294-311.

Harmeling CM, Moffett JW, Arnold MJ, Carlson BD. Toward a theory of customer engagement marketing. *J Acad Mark Sci.* 2017;45(3):312-35.

Holmlund M, Van Vaerenbergh Y, Ciuchita R, Ravald A, Sarantopoulos P, Ordenes FV, et al. Customer experience management in the age of big data analytics: A strategic framework. *J Bus Res.* 2020;116:356-65.

Becker L, Jaakkola E. Customer experience: Fundamental premises and implications for research. *J Acad Mark Sci.* 2020;48(4):630-48.

Homburg C, Jozić D, Kuehnl C. Customer experience management: toward implementing an evolving marketing concept. *J Acad Mark Sci.* 2017;45(3):377-401.

Lemmens A, Gupta S. Managing churn to maximize profits. *Mark Sci.* 2020;39(5):956-73.

Hollebeek LD, Srivastava RK, Chen T. SD logic-informed customer engagement: integrative framework, revised fundamental propositions, and application to CRM. *J Acad Mark Sci.* 2019;47(1):161-85.

Amin A, Al-Obeidat F, Shah B, Adnan A, Loo J, Anwar S. Customer churn prediction in telecommunication industry using data certainty. *J Bus Res.* 2019;94:290-301.

Amin A, Shah B, Khattak AM, Moreira FJ, Ali G, Rocha A, et al. Cross-company customer churn prediction in telecommunication: A comparison of data transformation methods. *Int J Inf Manag.* 2019;46:304-19.

Shirazi F, Mohammadi M. A big data analytics model for customer churn prediction in the retiree segment. *Int J Inf Manag.* 2019;48:238-53.

Liang LJ, Choi HC, Joppe M. Exploring the relationship between satisfaction, trust and switching intention, repurchase intention in the context of Airbnb. *Int J Hosp Manag.* 2018;69:41-8.

Tsai PH, Tang JW. Consumers' switching intention towards E-commerce platforms' store-to-store pickup services: The application of the extended PPM model. *J Retail Consum Serv.* 2023;75:103535.

Kumar V, Rajan B, Gupta S, Pozza ID. Customer engagement in service. *J Acad Mark Sci.* 2019;47(1):138-60.

Venkatesan R. Executing on a customer engagement strategy. *J Acad Mark Sci.* 2017;45(3):289-93.

de Oliveira Santini F, Ladeira WJ, Pinto DC, Herter MM, Sampaio CH, Babin BJ. Customer engagement in social media: A framework and meta-analysis. *J Acad Mark Sci.* 2020;48(6):1211-28.

Meire M. Customer comeback: Empirical insights into the drivers and value of returning customers. *J Bus Res.* 2021;127:193-205.

Kumar V, Leszkiewicz A, Herbst A. Are you back for good or still shopping around? Investigating customers' repeat churn behavior. *J Mark Res.* 2018;55(2):208-25.

Chen Y, Mandler T, Meyer-Waarden L. Three decades of research on loyalty programs: A literature review and future research agenda. *J Bus Res.* 2021;124:179-97.

Gabel S, Guhl D. Comparing the effectiveness of rewards and individually targeted coupons in loyalty programs. *J Retail.* 2022;98(3):395-411.

Danaher PJ, Sajtos L, Danaher TS. Tactical use of rewards to enhance loyalty program effectiveness. *Int J Res Mark.* 2020;37(3):505-20.

Ascarza E, Ebbes P, Netzer O, Danielson M. Beyond the target customer: Social effects of customer relationship management campaigns. *J Mark Res.* 2017;54(3):347-63.

Li Y, Hou B, Wu Y, Zhao D, Xie A, Zou P. Giant fight: Customer churn prediction in traditional broadcast industry. *J Bus Res.* 2021;131:630-9.

Wu X, Li P, Zhao M, Liu Y, Crespo RG, Herrera-Viedma E. Customer churn prediction for web browsers. *Expert Syst Appl.* 2022;209:118177.

Haddadi SJ, Farshidvard A, dos Santos Silva F, dos Reis JC, da Silva Reis M. Customer churn prediction in imbalanced datasets with resampling methods: A comparative study. *Expert Syst Appl.* 2024;246:123086.

Rahman S, Janssens B, Bogaert M. Profit-driven pre-processing in B2B customer churn modeling using fairness techniques. *J Bus Res.* 2025;189:115159.