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The Behavioral Fingerprint of Brand Loyalty: Predicting Switching Intentions through Digital Interaction Patterns and Emotional Engagement

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Abstract:
Brand loyalty encompasses both attitudinal commitment and behavioral patterns, yet these dimensions may not fully capture customers' evolving propensity to switch. This study develops an integrative framework for predicting switching intentions from digital interaction patterns and emotional engagement. It brings together research on customer behavior prediction from digital data and evidence that brand experience and emotional attachment are associated with loyalty. The framework treats interaction signals as behavioral indicators and emotional engagement as a relational dimension, considering their joint relevance to switching intentions. By connecting observable digital activity with consumers' emotional responses to brands, the proposed approach offers a basis for studying loyalty as a dynamic pattern rather than a fixed outcome.

Keywords: *Brand Loyalty; Switching Intentions; Digital Interactions; Emotional Engagement; Customer Behavior Prediction; Brand Experience.*

I. INTRODUCTION

Customer loyalty is commonly understood through both attitudinal commitment and purchasing behavior, although defining and measuring the construct remains challenging. In digital settings, researchers have used clickstream data to predict purchase intentions and machine-learning methods to identify customer churn. These approaches establish the relevance of observable interaction and behavioral data to predicting customer outcomes, while leaving room to consider how such signals relate to customers' emotional ties with brands.

Brand experience encompasses sensory, affective, cognitive, and behavioral responses to brand-related stimuli and has been associated with loyalty. Research also links emotional brand attachment to loyalty and identifies it as a pathway through which brand experience may influence that outcome. Building on these behavioral and relational perspectives, this study develops an integrative framework for examining switching intentions through digital interaction patterns and emotional engagement, treating the former as behavioral indicators and the latter as a relational dimension.

II. THE STRATEGIC PROBLEM OF DETECTING SWITCHING BEFORE CHURU

Brand switching is usually recorded after the economically relevant decision has occurred, when a customer cancels, purchases from a competitor, or ceases activity. This retrospective definition is inadequate for intervention because digital traces can reveal changing information search, reduced purchasing, complaint activity, and attraction to alternatives before observed defection. Earlier online-service research distinguished continuers from switchers using behavioral, attitudinal, and demographic information, including usage, satisfaction, involvement, risk propensity, income, and education [1]. The managerial problem is therefore to estimate **switching intention** as a forward-looking state rather than equate it with realized churn. [2]

Digital interaction records expand this possibility. Clickstream sequences, product comparisons, app sessions, customer-service contacts, social-media reactions, and transaction histories describe what customers do across touchpoints. These signals remain incomplete because an interaction may express curiosity, routine use, dissatisfaction, or a search for alternatives. Online purchase studies likewise show that purchase intention and actual purchase are distinct endpoints, requiring models that connect platform engagement with customer characteristics and subsequent transactions [3]. A useful prediction system must there fore combine observable conduct with survey-based measures of trust, commitment, experience, and emotional attachment. [4]

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Research Questions, Contributions, and Proposed Behavioral-Fingerprint Model

This paper asks three questions: which digital and transactional patterns precede switching intention; whether emotional engagement adds predictive value beyond observable behavior; and whether model performance and predictors vary across industries, platforms, and customer profiles. It proposes a **behavioral fingerprint** as a time-indexed representation of interaction frequency, recency, channel movement, purchase continuity, service friction, social participation, and emotional responses. The design follows evidence that multichannel customer data can predict domain-specific psychological traits with moderate to high accuracy when linked to survey measures [5].

The proposed contribution is an integrated prediction framework rather than a single algorithm. It combines loyalty theory, push-pull-mooring explanations of switching, and comparative models ranging from logistic regression to recurrent neural networks. The central expectation is that declining commitment, deteriorating experience, and attraction to alternatives will alter the meaning of otherwise ambiguous activity. The model consequently treats engagement as conditional: frequent interaction may indicate attachment, evaluation, complaint escalation, or stress-induced disengagement [6]. The following review establishes the constructs and mechanisms required to test that proposition.[7]

III. LITERATURE REVIEW

Measuring Brand Loyalty Across Attitudes, Behaviors, and Digital Contexts

Cognitive, Affective, and Conative Components of Brand Loyalty

Brand loyalty is best treated as a relationship construct containing evaluative, emotional, and behavioral components. Cognitive loyalty concerns beliefs about quality, credibility, value, or superiority; affective loyalty concerns liking, attachment, and commitment; conative loyalty concerns intention to continue, recommend, or resist alternatives. A hotel study operationalized these stages as cognitive-affective-conative attitudinal loyalty and found that satisfaction related to behavioral loyalty indirectly through the attitudinal sequence [8]. This distinction prevents purchase frequency from being interpreted as commitment when repeat behavior may result from convenience, habit, limited choice, or contractual constraints.

Measurement heterogeneity remains a persistent methodological problem. A review of 163 loyalty studies found that researchers use differing combinations of attitudes and purchase behaviors, with consequences for estimated links between loyalty-building strategies and performance [9]. Odin, Odin, and Valette-Florence separated repeat purchasing from **brand sensitivity**, arguing that repeated purchases alone do not establish a valid loyalty construct [10]. The implication for prediction is direct: a target labelled “loyal” should identify which aspect is measured, over what period, and against which alternatives.[11]

Affective and conative dimensions also mediate the relationship between experience and later behavior. Across cars, laptops, and sneakers, brand experience was associated with loyalty through affective commitment rather than through a simple direct pathway [12]. In banking, brand equity was linked to repeat purchase, willingness to pay, positive word of mouth, and switching intentions, with satisfaction partially mediating these relationships [13]. These findings support a layered outcome architecture in which switching intention is modeled separately from loyalty attitudes and observed retention.[14]

Behavioral Loyalty, Repurchase, Advocacy, and Willingness to Pay

Behavioral loyalty includes repeat purchase, retention, usage continuity, share of category spending, and resistance to competitor offers. Attitudinal loyalty includes advocacy and willingness to pay more, which may persist even when purchase opportunities are infrequent. In Internet services, credibility, confidence benefits, and special treatment benefits were associated with repurchase intention, word of mouth, and willingness to pay more, while satisfaction mediated several of these relationships [15]. Such measures represent distinct economic consequences and should not be collapsed into a single score without testing their measurement structure.

The literature also separates loyalty from advocacy. Online brand-community research linked customer experience to community engagement and then to word-of-mouth intention [16]. Social-media community research found that stronger relationships among customers, brands, companies, and other customers were associated with trust, which in turn related to loyalty [17]. These results suggest that contribution behaviors, such as reviewing, sharing, advising, and defending a brand, may identify relational investment, but they can also reflect controversy or dissatisfaction. Sentiment and interaction purpose are therefore needed to distinguish positive advocacy from negative publicity.[18]

Customer lifetime value requires this distinction because future margin depends on both buying probability and relationship quality. A customer with high historical spending but declining trust may have greater immediate value and greater switching exposure than a low-spending but stable customer. Existing research on customer lifetime value has consequently combined repurchase intention, willingness to pay more, and word of mouth as separate loyalty components [15]. A behavioral-fingerprint model should estimate each endpoint and then connect switching probability to expected revenue, rather than treating retention as the sole indicator of value.

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Online–Offline Differences in Loyalty Measurement and Customer Lifetime Value

Digital and physical environments generate different opportunities for observation and different forms of choice. In a comparison of more than 100 brands across 19 grocery categories, observed loyalty for high-share brands was greater than expected online, whereas small-share brands showed the reverse pattern; this relationship with market share did not appear in the traditional shopping environment [19]. Online loyalty may therefore reflect platform search, assortment visibility, saved preferences, delivery convenience, and lower switching friction, while offline loyalty may reflect store access and habitual shelf choice.[20]

Digital records also permit temporal measures that surveys cannot reconstruct reliably. Recency, interpurchase intervals, browsing depth, abandoned carts, channel migration, and service-contact sequences can be calculated repeatedly. Yet these measures may overstate psychological attachment because platform design generates interaction independently of brand preference. Online service research demonstrates why usage and attitudes should be modeled jointly: behavioral usage, satisfaction, involvement, and risk propensity discriminated between continuers and switchers, but no single class of variable was sufficient [1].

The literature supports a measurement architecture with three linked layers: attitudinal loyalty, behavioral loyalty, and economic value. A survey captures cognitive, affective, and conative evaluations; transactions capture purchase and retention; customer-level financial records estimate margin or lifetime value. The layers should remain analytically distinct while allowing mediation and interaction tests. This architecture prepares the next section, which explains how digital engagement and emotional attachment may generate, sustain, or undermine those loyalty dimensions.

Study context	Loyalty endpoint	Main design	Measurement implication
Hospitality	Cognitive, affective, conative, and behavioral loyalty	Survey and structural model [8]	Purchase frequency should be interpreted through attitudinal stages
Internet service	Repurchase, word of mouth, willingness to pay more	Online survey and PLS-SEM [15]	Economic and advocacy outcomes are distinct
Grocery retail	Observed online and offline brand choice	Matched purchase-panel comparison [19]	Channel context changes expected loyalty
Cross-study loyalty research	Strategy, loyalty, and performance relationships	Meta-analysis of 163 studies [9]	Construct and operational heterogeneity affects inference

Literature Review: Digital Engagement, Brand Experience, and Emotional Attachment as Loyalty Mechanisms

Behavioral, Cognitive, and Emotional Dimensions of Digital Brand Engagement

Digital brand engagement refers to the customer's investment in brand-related interactions, but the literature distinguishes psychological state from its behavioral manifestations. France, Merrilees, and Miller conceptualized customer-brand engagement as a psychological state and treated observable behaviors as consequences rather than synonyms [21]. Dwivedi defined engagement through vigor, dedication, and absorption, finding that it explained additional variation in loyalty intentions beyond value, quality, and satisfaction among mobile-phone consumers [22]. These formulations caution against defining engagement as clicks alone.[23]

A multidimensional digital measure should include behavioral, cognitive, and emotional components. Behavioral engagement includes viewing, clicking, commenting, sharing, creating content, participating in communities, and using branded applications. Cognitive engagement includes attention, information processing, advice seeking, and evaluation. Emotional engagement includes enthusiasm, affection, identification, and relational involvement. Research on social media engagement operationalized consumption, contribution, and creation as distinct behavioral dimensions, with creation having the strongest association with brand intimacy, followed by consumption [24].

Digital engagement is shaped by both customer motives and platform design. Online brand-community research identified eleven motivations for continued participation, indicating that interaction can arise from information, identity, social connection, entertainment, or intrinsic interest [25]. Studies of social-media brand posts found that interactivity and novelty encouraged engagement, which was associated with brand love and customer-brand identification [26]. A social-media engagement prediction study further showed that human-designed post features combined with BERT-extracted textual features improved prediction of engagement responses [27]. The behavioral fingerprint should therefore encode content and context, not merely event counts.

Longitudinal evidence qualifies cross-sectional conclusions. In a three-wave study, customer engagement and social-media stickiness fluctuated after purchase, and engagement had cross-lagged effects on later stickiness; firm social-media activities did not directly produce later stickiness [28]. This finding supports lagged features and repeated measurement. A customer may be highly engaged during evaluation but less engaged after purchase, or may remain active because of unresolved problems. Time ordering is thus necessary for separating engagement as a mechanism from engagement as a contemporaneous symptom.

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Brand Experience, Trust, Commitment, Intimacy, and Self-Brand Connection

Brand experience encompasses sensations, feelings, cognitions, and behavioral responses elicited by brand-related stimuli. Its validated dimensions are sensory, affective, intellectual, and behavioral [29]. In online settings, perceived usefulness and trust were associated with positive brand experience, which related to satisfaction, behavioral intentions, and online brand relationships [30]. Digital experience is consequently both instrumental and relational: a usable interface may reduce effort, while trustworthy communication may create confidence in future exchanges.[31]

Trust and commitment frequently function as intervening mechanisms. In online services, engagement and experience were associated with trust and commitment, while loyalty effects operated through commitment [32]. Social-media marketing activities were associated with commitment, trust, satisfaction, and loyalty among telecommunications customers, with relationship-quality dimensions mediating the connection between marketing activities and loyalty [33]. Social presence alone did not directly predict commitment or loyalty in one social-commerce study; trust fully mediated those relationships [34]. These results imply that interaction volume has limited meaning without evidence that the customer interprets the interaction as credible and relationship-consistent.

Emotional attachment adds a deeper relational dimension. Smartphone research found that brand experience supported loyalty through brand passion, self-brand connection, and brand affection [35]. In automobile consumers, attachment was associated with brand love, while brand love related to trust and interest in continuing the relationship [36]. Social-media brand research similarly linked emotional attachment to brand equity through credibility and satisfaction [37]. Emotional variables may therefore identify resilience against ordinary service failures, but they should not be assumed to eliminate switching when alternatives become attractive.

Digital platforms can intensify relational experience. Digital banking research reported a direct association between emotional attachment and bank loyalty and an indirect path through psychological engagement with websites or applications; platform type moderated the strength of the attachment-engagement relationship [38]. Metaverse research among Gen Z participants associated interactivity with trust, brand knowledge, and attachment, followed by active engagement and real-world purchase intention [39]. These studies are context-specific and largely survey-based, so they support construct specification more strongly than universal causal claims.

Positive and Negative Engagement: When Interaction Strengthens or Undermines Loyalty

Engagement is not inherently beneficial. Positive engagement can produce trust, intimacy, advocacy, and usage intention, but high interaction may also impose cognitive and emotional demands. An experimental destination-brand study with 278 consumers found that high online engagement increased perceived stress, followed by disengagement and destination-switching intention through sequential mediation; moderate engagement produced more favorable outcomes than low or high engagement [6]. This evidence directly challenges a monotonic assumption that more activity always predicts retention.

The valence of engagement must therefore be measured. Positive engagement includes affirmative thoughts, favorable feelings, and constructive behaviors, whereas negative engagement includes unfavorable thoughts, emotions, and brand-related actions [40]. Complaint frequency, hostile comments, repeated help-seeking, and negative sentiment may indicate intense involvement rather than indifference. A model using only event counts could classify an angry, highly active customer as loyal. Sentiment, issue resolution, response delay, and subsequent purchase behavior are needed to identify the direction of the relationship. [41]

Emotions also modify the meaning of established equity drivers. Across 102 firms in eighteen service industries, positive and negative emotions each added explanatory power for loyalty intentions. Positive emotions weakened the positive association between customer-equity drivers and loyalty intentions, whereas negative emotions strengthened the association for brand and relationship equity [42]. This counterintuitive result indicates that emotional effects are conditional rather than uniformly additive. The next review applies this insight to switching theory and predictive modeling.

Literature Review: Switching Intentions and Predictive Modeling of Customer Behavior

Push–Pull–Mooring Drivers of Brand and Service Switching

The **push-pull-mooring** framework distinguishes forces that push customers away from the current provider, pull them toward alternatives, and moor them through switching costs or relational ties. In telecommunications, service-quality deterioration was a major push factor, and churners were more sensitive to service quality than non-churners [43]. In smartphone markets, regret operated as a push factor, alternative attractiveness and subjective norms operated as pull factors, while switching costs, emotional commitment, and brand-community engagement reduced switching intention; variety seeking increased it [44].

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This framework integrates service experience with relationship resources. Complaints, failed interactions, price dissatisfaction, and declining perceived quality represent push signals. Competitor browsing, alternative comparison, social recommendations, and exposure to attractive offers represent pull signals. Contract duration, accumulated rewards, habit, emotional commitment, and community membership represent mooring signals. The same digital event can belong to different categories depending on sequence and context: competitor search may reflect routine information gathering or active migration, while a complaint may be resolved successfully or become a trigger for exit.[45]

Switching intention is also distinct from realized switching. Earlier online-service research examined continuers and switchers using usage, satisfaction, involvement, risk propensity, and demographic variables [1]. The PPM studies primarily use survey-based intention or observed churn, while predictive CRM research estimates a customer-level probability of future churn and recommends retention action [46]. A rigorous study should report both intention prediction and behavioral validation when future transaction or cancellation data are available.

Clickstream, Purchase, Social-Media, and Multichannel Signals of Intent

Digital prediction research demonstrates that short-term behavioral sequences contain information about near-term decisions. A clickstream model using 33,339,730 clicks from 445,336 sessions reported an F1 score of 0.9031 for anonymous purchase behavior and performed best with a two-day sliding window [47]. Another large e-commerce study used 33,040,175 click records and 1,177,769 buy records; its machine-learning and deep-learning models achieved approximately 72 to 75 percent accuracy, with a six-day window performing best for the machine-learning models and a 50-layer LSTM producing the strongest deep-learning result [48]. The difference in window length and endpoint performance illustrates why temporal design cannot be transferred mechanically across datasets.

Purchase histories offer complementary information. In non-contractual settings, recency, frequency, monetary value, and time-based features were updated monthly; gradient tree boosting achieved an accuracy of 89 percent and an AUC of 0.95 for next-month purchase prediction [49]. Online tourism research similarly ranked multiplex behavior variables by predictive marginal value and used partial-dependence plots to interpret their relationship with purchase [50]. These findings support rolling features, but purchase prediction is not equivalent to switching prediction. A customer may continue purchasing while actively considering another brand.

Social signals add relational and affective information. Interactive or novel brand posts can generate engagement and strengthen brand-love and identification outcomes [26]. Social-media communications have also been linked to perceived value, online community engagement, and travellers' switching intentions [51]. Text, sentiment, response direction, creator status, and community participation should therefore be retained rather than reduced to a binary interaction indicator. Multichannel data can additionally support psychological-trait inference, although moderate predictive accuracy does not establish that inferred traits are stable or causally responsible for switching [5].

Logistic Regression, Random Forest, Deep Learning, and Hybrid Prediction Approaches

Model selection should balance discrimination, calibration, interpretability, and temporal robustness. **Logistic regression** provides coefficient-level direction and odds-based interpretation, making it suitable for testing PPM hypotheses and estimating incremental emotional effects. In a telecommunications comparison of logistic regression, support vector machines, random forest, and decision trees, logistic regression achieved the highest prediction accuracy [43]. In contrast, an e-commerce comparison found that random forest exceeded logistic regression, with reported accuracy of 95 percent and ROC-AUC of 0.97 compared with 90 percent and 0.88, respectively; class-one recall remained lower than majority-class recall for both models [52].
Tree ensembles can represent nonlinear thresholds and interactions without requiring a fully specified equation. Gradient boosting performed best in one non-contractual purchase setting [49], while an ensemble CRM framework combining random forest, gradient boosting, and support vector machines reported accuracy of 0.89 and ROC-AUC of 0.91 in telecommunications [53]. Deep learning is most defensible when event sequences, text, or very large samples justify its parameter complexity. Deep learning outperformed several conventional methods for online purchase prediction in more than 50,000 web sessions [3], whereas another very large clickstream comparison found similar accuracy between recurrent and LSTM models and tree-based methods [48], [54].

Hybrid designs address different sources of uncertainty. A churn framework combined statistical customer-alive probabilities with machine learning and behavioral clustering, reducing the risk of misclassifying customers with long consumption cycles as churned [55]. Hybrid SEM-ANN analysis has also been used to connect psychological needs, cognitive engagement, affective engagement, behavioral engagement, and well-being in digital platforms [56]. The proposed study will compare interpretable and flexible models under identical temporal splits, then assess whether added complexity yields useful improvement rather than merely higher in-sample fit.

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Model family	Evidence base	Reported endpoint and result	Relevance to switching prediction
Logistic regression	Telecom churn comparison [43]	Highest accuracy among tested models	Interpretable baseline for PPM effects
Random forest	E-commerce churn comparison [52]	Accuracy 95%, ROC-AUC 0.97	Captures nonlinear customer patterns
Gradient boosting	Non-contractual purchase prediction [49]	Accuracy 89%, AUC 0.95	Strong candidate for tabular recency and value features
Deep learning	Online purchase sessions [3]	Outperformed compared machine-learning methods	Represents high-dimensional interaction patterns
Hybrid statistical and machine learning	Dynamic churn framework [55]	Recall ranged from 0.56 to 0.72 in one dataset and 0.91 to 0.95 in another	Accommodates heterogeneous purchase cycles

Methods: Building a Multisource Behavioral-Fingerprint Prediction Framework

Data Architecture: Integrating Digital Interaction, Transactional, Survey, and Customer-Profile Data

The proposed architecture links four sources at the customer and timestamp level: digital interaction logs, transactions, surveys, and profile or CRM records. Digital logs include page views, searches, product comparisons, application sessions, email responses, social reactions, community contributions, customer-service contacts, and competitor-related content exposure where ethically and technically observable. Transactional data include order dates, categories, value, returns, cancellations, channel, discount use, and interpurchase intervals. Survey data measure loyalty, experience, trust, commitment, attachment, satisfaction, involvement, perceived alternatives, and switching intention. CRM data provide tenure, contract status, service plan, channel history, and permitted demographic or profile attributes.

A common customer key and event-time standard are required before feature construction. Each event should retain source channel, event type, object or category, session identifier, and outcome status. The data model should preserve raw records in an immutable layer, create a cleaned event layer, and generate customer-period features in an analytical layer. Multichannel customer research demonstrates the value of joining survey-based psychological measures to CRM behavior rather than treating either source as sufficient [5]. The design should nevertheless separate prediction variables from intervention records to prevent post-outcome leakage.[57]

The unit of analysis will be a customer-period observation, such as a weekly or monthly snapshot, followed by an outcome window. A customer may therefore contribute repeated observations, but all predictors must precede the switching-intention assessment or observed switch. The architecture should support both anonymous-session models for short-term purchase behavior and identified-customer models for relational switching risk. Research on clickstream prediction and monthly purchase updating supports the use of sliding or rolling windows, while the reported variation in optimal windows requires empirical selection within each validation fold [47], [49].

Operationalizing Switching Intention, Brand Loyalty, Engagement, Experience, and Emotional Attachment

The primary target is a validated switching-intention index measured through items concerning likelihood of changing provider, search for alternatives, reduced future preference, and intention to purchase from a competitor. A binary target can be defined for classification, while an ordinal or continuous score can preserve information for regression and calibration analysis. When possible, the survey target should be followed by an observed behavioral outcome, such as cancellation, competitor purchase, nonrenewal, or sustained category absence. This distinction follows evidence that purchase intention does not necessarily become an actual retail purchase [3].

Brand loyalty will be modeled as separate latent dimensions: cognitive evaluation, affective attachment or commitment, conative continuation intention, repeat behavior, advocacy, and willingness to pay more. Scale items should be assessed for reliability, convergent validity, discriminant validity, and measurement invariance across platform and industry groups. The cognitive-affective-conative sequence used in hospitality research supports retaining stages rather than collapsing them [8]. Behavioral indicators will include share of purchases, recency, retention duration, repeat interval stability, and competitor substitution where observable.

Digital engagement will be represented by behavioral frequency and diversity, cognitive indicators from information seeking, and emotional or valenced indicators from survey responses and text analysis. Consumption, contribution, and creation provide a defensible behavioral taxonomy for social platforms [24]. Brand experience will use sensory, affective, intellectual, and behavioral dimensions [29]. Emotional attachment will include brand affection, passion, self-brand connection, and relational commitment, because smartphone research connects these dimensions to loyalty rather than treating attachment as a single undifferentiated feeling [35].

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Feature Engineering, Missing-Data Treatment, Class Imbalance, and Temporal Validation

Feature engineering will calculate recency, frequency, duration, intensity, diversity, volatility, and sequence features for each channel. Examples include days since last visit, rolling session count, ratio of complaint to purchase events, abandoned-cart rate, competitor-comparison frequency, negative-to-positive sentiment ratio, number of channels used, and change from the customer's prior baseline. Interaction terms will represent whether high engagement occurs with declining experience, whether trust buffers service friction, and whether commitment moderates competitor exposure. Sequence features may be encoded through transition counts or recurrent models, but all transformations must use information available before the prediction time. [58]

Missingness will be diagnosed by source, customer type, channel, and outcome group. Structural missingness, such as the absence of an app for a non-app customer, differs from nonresponse or logging failure and should be encoded accordingly. Survey scales may use prespecified item-level scoring rules, while behavioral variables may receive transparent imputation or missingness indicators. Imputation parameters must be fitted within the training data only. The use of inferred psychological traits requires special caution because prediction error may be correlated with customer segment and may reproduce existing data inequalities [5].

Switching is likely to be less frequent than continuation, so accuracy alone is inadequate. Training data will use class weights or resampling within the training partition, while validation and test sets will preserve the observed prevalence. Precision, recall, F1, area under the ROC curve, area under the precision-recall curve, calibration, and expected intervention value will be reported. Temporal validation will train on earlier periods and test on later periods, with customer-level separation where leakage is possible. Dynamic churn research shows that fixed churn periods can misclassify customers with longer consumption cycles, supporting customer-specific observation windows and sensitivity analysis [55].

Comparative Model Specification and Evaluation Metrics

Four model classes will be estimated from the same feature sets: penalized logistic regression, random forest, gradient boosting, and sequence-based deep learning. A behavior-only specification will include digital, transaction, service, and profile variables. An emotion-augmented specification will add trust, commitment, experience, attachment, sentiment, and switching-attitude measures. A full interaction specification will add theoretically selected product terms. This nested design tests incremental predictive value rather than comparing unrelated feature spaces.

Logistic regression will provide coefficients, confidence intervals, calibration, and odds-ratio interpretation. Random forest and gradient boosting will be tuned through nested temporal validation, with permutation importance and partial-dependence or accumulated-local-effect plots used for interpretation. Recurrent models will receive ordered event sequences and static profile variables, with regularization and early stopping determined within training data. Deep learning should be retained only if it improves out-of-time discrimination or calibration enough to justify reduced transparency; evidence across purchase studies indicates that its advantage is context-dependent [3], [48].

Evaluation will prioritize recall at an operationally acceptable precision because missed switchers and unnecessary interventions have different costs. ROC curves describe ranking across thresholds, whereas precision-recall curves are more informative under class imbalance. Calibration plots will compare predicted and observed switching rates by risk decile. Confusion matrices will report false positives and false negatives at the selected intervention threshold. Nested-model comparisons, bootstrap intervals, subgroup performance, and ablation tests will determine whether emotional information contributes beyond behavior and whether gains persist across channels. [58]

Results: Identifying the Behavioral and Emotional Signature of Switching Intentions

Descriptive Statistics of Interaction Patterns, Loyalty Profiles, and Switching-Intention Groups

The descriptive analysis will begin with customer counts, observation periods, channel coverage, transaction density, survey completion, missingness, and switching-intention prevalence. Because the source papers do not report the present study's sample, no numerical sample characteristic can be stated in advance. The final manuscript should report means and standard deviations for approximately symmetric variables, medians and interquartile ranges for skewed activity measures, and counts with percentages for categorical variables. Each statistic must specify whether it refers to customers, customer-period observations, sessions, transactions, or survey respondents.

Switching-intention groups will be compared on recency, interaction frequency, channel diversity, complaint activity, competitor searches, purchase continuity, loyalty dimensions, trust, commitment, brand experience, and emotional attachment. The analysis should distinguish low activity from negative activity. A customer with fewer sessions may be stable because purchases are infrequent, whereas a customer with many sessions and repeated unresolved complaints may be at elevated risk. This distinction follows the finding that high online destination engagement can increase stress and disengagement rather than loyalty [6].

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Descriptive tables should report standardized differences alongside significance tests because large repeated datasets can make trivial differences appear statistically significant. Correlation analysis will identify overlap among loyalty, engagement, experience, trust, commitment, and attachment before multivariable modeling. High correlations are theoretically expected because experience can relate to trust, commitment, attachment, and loyalty through mediated pathways [32], [35]. They should not be interpreted as evidence that the constructs are interchangeable.[59]

Customer profiles should be summarized by tenure, contract or subscription status, purchase cycle, channel preference, and observed service contact. Profiles with long consumption cycles require separate interpretation because a long gap between purchases is not necessarily churn [55]. Cross-tabulations will show whether survey respondents differ from nonrespondents in activity or value. If they do, emotional predictors may be subject to selection bias, and behavior-only models may be needed for customers without survey data.

Predictive Performance Across Statistical, Machine-Learning, and Deep-Learning Models

The results section will compare models using identical temporal partitions and target definitions. The first table should report ROC-AUC, precision, recall, F1, PR-AUC, calibration error, and threshold-specific intervention yield. Accuracy will be included for comparability but not used as the primary criterion under class imbalance. Published comparisons demonstrate why model rankings cannot be assumed in advance: logistic regression performed best in one telecommunications dataset [43], while random forest performed better than logistic regression in an e-commerce churn dataset [52], [60].

The behavior-only logistic model will establish whether conventional predictors such as recency, purchase continuity, service quality indicators, and usage change identify switching risk. Its coefficients will show direction, but correlated features and repeated observations require clustered uncertainty or resampling at the customer level. The tree models will test nonlinearities, such as a threshold at which complaint frequency or competitor search becomes associated with higher risk. Gradient boosting is a plausible benchmark because it achieved strong performance for future purchase prediction using dynamic customer features [49]. The sequence model will be evaluated against the same outcome window, not against a more favorable endpoint. Deep learning may improve ranking when event order, text, and high-dimensional interactions contain information that aggregate features lose. Yet published evidence is mixed: deep learning outperformed conventional approaches in one online purchase study [3], while another large clickstream comparison reported similar accuracy for recurrent, LSTM, and machine-learning models [48]. The present comparison should therefore emphasize out-of-time performance, calibration, and operational usefulness rather than complexity or training accuracy.

A hybrid model may combine a customer-alive probability, behavioral segment, and machine-learning switching score. This is appropriate when customers differ in purchase-cycle length or contractual exposure. The hybrid churn literature used statistical survival information to define a dynamic churn line and then applied machine learning to customer segments [55]. Its contribution in this study would be assessed through calibration and recall among long-cycle customers, not merely through aggregate AUC.

Incremental Predictive Value of Emotional Engagement Beyond Observable Behavior

The central test compares behavior-only and emotion-augmented models. Improvement should be reported through changes in PR-AUC, ROC-AUC, calibration, recall at fixed precision, and decision-curve or intervention value. Emotional engagement will be considered incrementally useful if it improves out-of-time predictions after accounting for recency, frequency, transactions, service friction, profile, and channel behavior. The test should also determine whether emotional variables improve calibration even when ranking changes little.

The literature supports this comparison but does not establish its magnitude for the proposed data. Brand engagement explained loyalty intentions beyond value, quality, and satisfaction in mobile-phone consumers [22]. Brand experience has been associated with loyalty through affective commitment across several product categories [12]. Online-service research likewise found that engagement and experience related to trust and commitment, with loyalty effects transmitted through commitment [32]. These findings imply that emotional measures may identify latent relationship strength that event counts cannot observe.

Incremental value should be tested separately for self-reported emotional measures, text-derived affect, and platform-derived proxies. Survey attachment may be predictive but unavailable for many customers; text sentiment may be frequent but ambiguous; repeated complaints may reflect negative involvement rather than emotional detachment. The model should report missing-survey performance and use nested ablation to determine whether a small emotional module produces stable gains. Multichannel psychological-trait prediction demonstrates feasibility but also indicates that inferred traits vary in predictability across domains [5].

The analysis must avoid interpreting predictive contribution as causal protection against switching. Emotional attachment may be a consequence of prior positive experience, a correlate of high usage, or a response to recent brand communication. The reported interaction between positive and negative emotions and customer-equity drivers further suggests that emotional effects can strengthen or weaken existing loyalty relationships depending on valence and equity type [42]. Results should therefore present incremental prediction, mediation-consistent associations, and temporal precedence as separate claims.[61]

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Interaction Effects Among Engagement Frequency, Brand Experience, Trust, Commitment, and Switching Risk

Interaction analysis will test whether engagement frequency changes meaning across levels of experience and relationship quality. The first hypothesis is curvilinear or threshold-like: moderate engagement may accompany healthy involvement, whereas very high engagement combined with stress, unresolved complaints, or negative sentiment may precede switching. This specification is supported by experimental evidence that moderate destination-brand engagement produced more favorable outcomes than high engagement, which increased stress and sequentially predicted disengagement and switching intention [6].

The second hypothesis concerns experience and commitment. Positive brand experience may reduce switching risk primarily when it produces affective commitment, rather than through a direct effect. Evidence across cars, laptops, and sneakers supports this mediated structure [12]. The analysis will estimate whether commitment attenuates the association between declining experience and switching intention, while recognizing that a cross-sectional survey cannot prove the complete temporal mechanism.

The third hypothesis concerns trust. Engagement may be protective when customers regard the brand as credible and dependable, but ineffective or harmful when interaction increases exposure to inconsistent information. Online service studies associate engagement and experience with trust and commitment [32], while social-commerce research found that trust fully mediated relationships between social presence and commitment or loyalty [34]. The prediction model should therefore include engagement-by-trust and experience-by-trust terms, with marginal-effect plots rather than isolated coefficients.

The fourth hypothesis concerns commitment and alternatives. Emotional commitment and brand-community engagement were associated with lower smartphone switching intention, whereas alternative attractiveness and variety seeking were associated with higher intention [44]. A high-commitment customer may still switch when competitor attraction and service failure jointly exceed relational resistance. The final model should display predicted risk across combinations of engagement, experience, trust, commitment, and alternative search, using confidence bands and subgroup checks. @

Planned Evidence Displays: Feature-Importance Table, Correlation Matrix, ROC and Precision–Recall Graphs, Confusion Matrix, and Behavioral-Fingerprint Diagram

The evidence displays will connect descriptive, predictive, and interpretive results. Table 1 will report variable definitions, source systems, time windows, missingness, and hypothesized direction. Table 2 will compare model metrics across behavior-only, emotion-augmented, and full interaction specifications. A feature-importance table will rank predictors separately for logistic coefficients, permutation importance, and tree-based explanations, because rankings from different algorithms are not directly equivalent. Partial-dependence plots will show nonlinear effects for recency, competitor search, complaint intensity, and engagement frequency, following the interpretive use of predictive marginal values in online tourism forecasting [50].

The correlation matrix will be restricted to customer-level or appropriately aggregated constructs and will distinguish observed features from latent scale scores. ROC and precision-recall graphs will use the untouched temporal test set. The latter is necessary because a model can have a high ROC-AUC while producing poor precision when switching is rare. A confusion matrix will be reported at the intervention threshold selected from cost or capacity assumptions, with false-positive and false-negative consequences stated explicitly.

The behavioral-fingerprint diagram will show the path from multisource events to rolling features, psychological constructs, model scores, and observed or intended switching outcomes. It should make clear that digital activity is not itself loyalty, and that emotional variables may mediate or modify its meaning. The structure is represented below.

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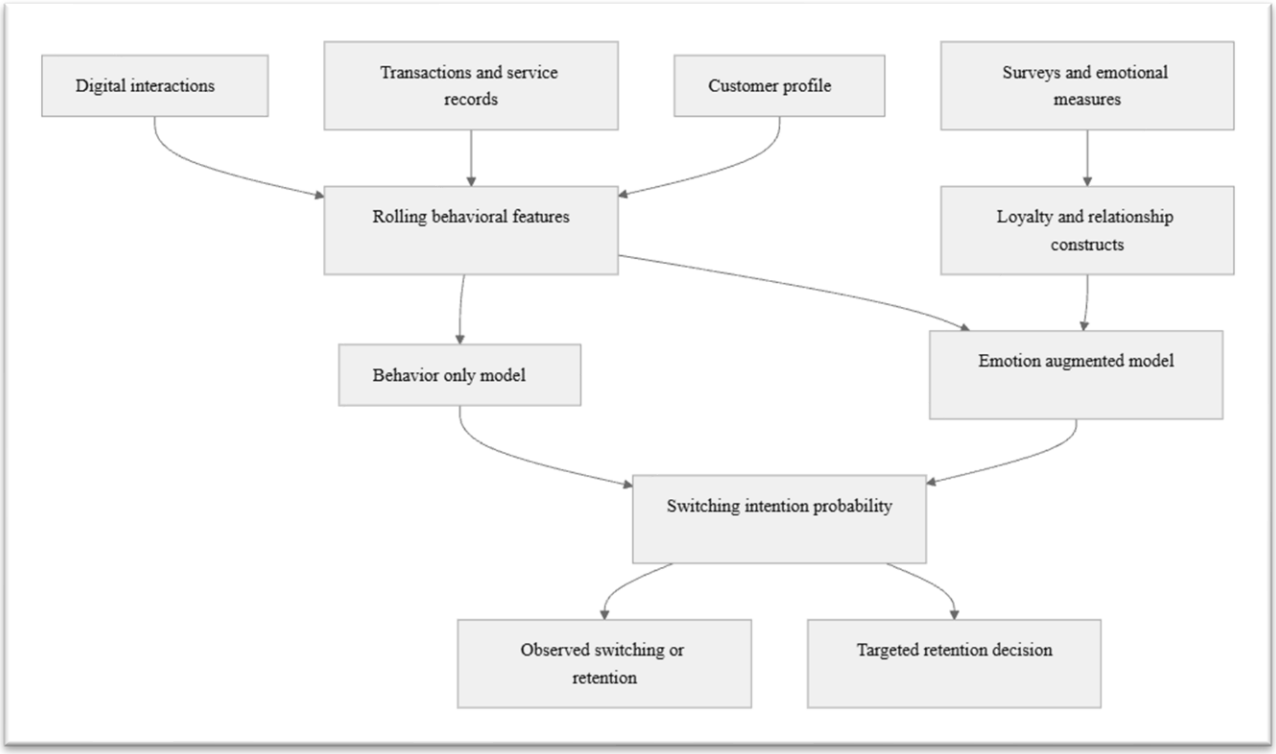


Diagram 1

The displays should be accompanied by uncertainty intervals, subgroup performance, and data-availability notes. This is especially important because online and offline loyalty patterns differ [19], engagement can fluctuate longitudinally [28], and high activity can signal either attachment or stress [6]. Together, the displays will show whether the behavioral fingerprint is a stable relational signature, a context-dependent risk profile, or a mixture of both.

Discussion: Interpreting Loyalty Signals, Predictive Accuracy, and the Limits of Digital Behavioral Inference

Why High Engagement Does Not Always Equal Loyalty

Engagement intensity should not be treated as a direct proxy for loyalty. Digital activity may reflect satisfaction and identification, but it may also indicate complaint escalation, uncertainty, comparison, or effort required to resolve a service failure. Positive and negative forms of engagement differ in cognitive, emotional, and behavioral valence, even when both generate frequent observable interactions [40]. Experimental evidence from destination branding further suggests that high online engagement can increase perceived stress and disengagement, which subsequently raise switching intention, whereas moderate engagement produces more favorable outcomes [6]. Consequently, frequency, duration, and contribution require interpretation alongside sentiment, service context, and subsequent purchasing. Longitudinal evidence also shows that engagement and social-media stickiness fluctuate, limiting the validity of a single activity snapshot [28].

Behavioral Versus Emotional Predictors of Switching Intentions

Behavioral predictors offer scale and temporal precision, whereas emotional predictors clarify why a customer's activity may signal retention or defection. Recency, declining purchase frequency, complaints, competitor searches, and abandonment can identify proximate risk, as demonstrated by churn and purchase-prediction models using transactional and clickstream data [43], [47]. Yet behavior alone cannot distinguish exploratory browsing from emotionally motivated rejection. Brand experience affects loyalty through affective commitment across several product categories, while engagement and experience influence online loyalty through trust and commitment [12], [32]. Emotional attachment, self-brand connection, passion, and affection therefore add construct validity to a behavioral fingerprint, although emotions themselves may operate as mediators or moderators rather than independent causes [35], [42]. A useful model should consequently compare behavior-only and emotion-augmented specifications, rather than assume that the most observable variables are the most explanatory.

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Cross-Industry and Cross-Platform Generalizability of the Behavioral Fingerprint

Generalizability is constrained by category economics, switching costs, platform affordances, and the meaning of engagement. Telecom churn models emphasize service-quality deterioration and switching pressures, whereas non-contractual retail models rely more heavily on purchase timing and monetary history [43], [49]. Online and offline grocery purchasing also produce different loyalty patterns, with online loyalty varying by market share in ways not observed in the corresponding traditional environment [19]. Platform type changes the relationship between emotional attachment and psychological engagement in digital banking, while social-media communities connect engagement to loyalty through trust [34], [38]. These findings support a transferable architecture of recency, frequency, sentiment, experience, and relationship quality, but not universal coefficients or thresholds. External validation should therefore test transport across industries, channels, customer cohorts, and platform devices before operational deployment.

Privacy, Explainability, Bias, and Responsible Use of Psychological and Interaction Data

Inferring psychological traits from customer records creates a higher ethical burden than predicting a transaction. Multichannel models have demonstrated that traits such as price consciousness and need for interaction can be predicted with moderate to high accuracy, raising clear concerns about profiling and psychological targeting [5]. Responsible systems should minimize collection, document consent and purpose, separate prediction from diagnosis, and restrict sensitive inferences from automated decision rules. Explainability requires calibrated probabilities, feature-level explanations, temporal validation, and human review of recommended interventions; predictive importance does not establish psychological causation. Bias audits should compare calibration, recall, false-positive burden, and intervention outcomes across demographic and accessibility groups, while privacy safeguards should address the data risks associated with social platforms [37]. Such controls preserve the distinction between identifying risk and assigning motives, allowing retention actions to remain supportive rather than manipulative.

Conclusion: Toward Earlier, Emotion-Aware Detection of Brand-Switching Risk

Theoretical and Managerial Implications for Loyalty Management

The behavioral-fingerprint model extends loyalty research by treating switching risk as a time-varying relation between interaction patterns, experience, emotion, and commitment. It integrates behavioral loyalty with cognitive, affective, and conative dimensions, avoiding the measurement error that follows from equating repeat purchase with genuine loyalty. Managers should use declining activity, complaints, and competitor-oriented behavior as prompts for diagnosis, then tailor responses according to trust, commitment, and emotional attachment. This approach also aligns retention decisions with customer lifetime value, which depends on repurchase, willingness to pay, and word of mouth rather than one behavioral indicator. The managerial objective is therefore earlier, interpretable assistance, not maximal contact or indiscriminate intervention.

Research Gaps and Priorities for Longitudinal, Multichannel Prediction

Future research should replace predominantly cross-sectional evidence with repeated measures that distinguish temporary fluctuation from durable switching propensity. Cross-lagged findings already indicate that engagement and stickiness change over time, but the direction and conditions of these relationships remain unresolved. Studies should combine clickstream, transactions, service conversations, social content, surveys, and confirmed switching outcomes, while testing missingness, privacy constraints, and measurement invariance across platforms. Comparisons among logistic regression, tree ensembles, and sequence models should report calibration, precision-recall performance, subgroup error, and incremental value from emotional variables rather than accuracy alone. Field experiments are also needed to establish whether emotion-aware alerts improve retention without increasing pressure, surveillance, or unequal treatment.

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