

A Markov Chain-Based Framework for Predicting Dynamic Customer Behavior Using Transition Probability Modeling

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ABSTRACT: Markov chains provide a transparent probabilistic approach for modeling dynamic systems whose behavior evolves through discrete states over time. This study develops and empirically validates a Markov chain-based framework for predicting dynamic customer behavior from observed transaction histories. The proposed framework transforms time-stamped retail transactions into a monthly customer-state panel, defines interpretable behavioral states, estimates transition probability matrices, evaluates short-term and multi-step state movement, and derives long-run steady-state behavior. Using a two-year online retail transaction dataset as the empirical case, customer activity is represented through five states: inactive, at-risk, occasional, active, and loyal. After cleaning the data, the analysis uses 805,549 valid purchase records from 5,878 customers and constructs 92,679 consecutive customer-month transitions. The estimated transition matrix shows strong persistence in inactive behavior, substantial instability among occasional and active customers, and meaningful but limited loyalty persistence. The long-run steady-state distribution suggests that, without intervention, the system tends toward a high inactive-state share, indicating structural retention risk. Predictive validation using a holdout period shows that the Markov model achieves 75.59% one-step state prediction accuracy, outperforming a simple state-persistence baseline of 66.32%. The findings demonstrate that Markov chains can convert historical state movements into interpretable forecasts, identify stable and unstable behavioral states, and support retention-oriented decision-making. The framework is adaptable to other stochastic dynamic systems, including machine reliability, disease progression, educational performance, weather-state evolution, and financial behavior.

Keywords: Markov chains; probability; stochastic; customer behavior prediction.

I. INTRODUCTION

Dynamic systems rarely remain fixed. Customers move from exploration to repeated purchase, machines shift from normal operation to degradation, patients progress through health states, and learners move between achievement levels. These movements are often uncertain because future behavior depends on both observed patterns and random variation. Traditional descriptive analysis can summarize what has already happened, but it is less effective when the research objective is to estimate how a system may evolve from its current condition to a future condition.

Markov chains are particularly useful for this type of problem because they model change as a sequence of transitions among discrete states. Instead of assuming a single deterministic outcome, a Markov model estimates the probability that a system currently in one state will move to another state in the next time period. This makes the approach suitable for research problems in which the same unit is observed

repeatedly and can occupy a finite set of meaningful states. In customer analytics, these states may represent inactivity, risk, occasional engagement, active purchasing, or loyalty. In engineering reliability, they may represent normal, degraded, warning, failure, and repair states.

The present study focuses on customer behavior as the main empirical case because online retail transactions naturally generate longitudinal behavioral records. Each customer leaves a time-stamped sequence of purchasing activity that can be converted into state transitions. This structure provides a direct empirical basis for estimating transition probabilities and forecasting future states. More importantly, the transition matrix is interpretable: it shows which states are stable, which states are fragile, and which states are likely to lead to recovery or decline.

The research problem this paper addresses is that many predictive studies in customer behavior emphasize classification accuracy while paying less attention to dynamic movement between behavioral states. A model may predict whether a customer will churn, but it may not explain the path through which the customer moved from active purchasing to inactivity. Markov chains help solve this limitation by placing transition behavior at the center of the analysis. They do not simply label customers; they model the probability of behavioral movement over time.

This study therefore proposes a Markov chain-based framework for predicting dynamic customer behavior using transition probability modeling. The framework defines customer states from monthly purchasing activity, estimates one-step and multi-step state transitions, evaluates steady-state behavior, and validates future-state prediction on a temporal holdout period. The aim is not to replace advanced machine-learning models but to provide a transparent, mathematically grounded, and easy-to-interpret probabilistic framework for decision support.

II. LITERATURE REVIEW

Retention-oriented customer research provides the first foundation for the present Markov-chain framework. One study shows that targeting customers only because they are classified as high-risk may be ineffective when the underlying movement mechanism is not understood [1]. A broader retention-management review identifies customer retention as a decision process that requires careful attention to timing, response, profitability, and customer-state change [2]. Evidence from e-commerce churn classification further shows that predictive techniques can support churn detection but still require interpretable behavioral explanations [3]. Class-imbalance research is also important because inactive and low-activity customer-months often dominate transaction panels and may distort evaluation if majority states are not handled carefully [4].

Sequential transaction data and segmentation studies strengthen the empirical basis for dynamic customer-state modeling. The Online Retail II dataset is a large repeated-transaction source that allows observation of customers over time and the conversion of purchase histories into state sequences [5]. RFM-based segmentation research shows that recency, frequency, and monetary variables can be extracted from retail transactions to form meaningful behavioral groups [6]. Subscription-churn prediction using support vector machines demonstrates the predictive strength of classification approaches while also highlighting the need for more transparent state-movement interpretation [7]. A Markov-chain study of brand-switching behavior confirms that transition probabilities can explain movement across competing choices in online service settings [8].

Probability-based customer analytics provides the conceptual link between behavioral history and future-state prediction. Customer-base probability modeling has been positioned as useful for non-contractual settings where churn is not directly observed and must be inferred from purchasing behavior [9]. RFM and customer-lifetime-value analysis connect recency-frequency-monetary evidence with future value, supporting the use of behavioral states as predictive features [10]. A Markov decision-process approach provides a direct methodological precedent for treating customer behavior as movement among decision states [11]. Customer-lifetime-value research further shows that customer states should be interpreted not only as descriptive categories but also as indicators of future managerial value [12]. Computer-assisted churn-management research adds that historical behavior can support early warning, retention planning, and decision support [13].

Recent retail and e-commerce studies bring the literature closer to the present empirical design. Retail segment prediction using clustering and Markov modeling shows that transaction-based customer segments can be linked to future segment movement [14]. Data-mining evidence in telecommunications confirms that temporal customer-risk analysis can improve churn prediction [15]. Hidden Markov modeling in e-commerce provides a strong precedent for representing customers as latent or observable behavioral states [16]. Repeated customer-base summaries also support dynamic inference when customers are observed across multiple time points [17]. Improved telecom churn prediction through data-mining techniques reinforces the importance of extracting predictive information from longitudinal customer records [18].

Network, adaptive, path-based, and system-transition studies extend the relevance of Markov-chain modeling beyond simple retail segmentation. Network-based churn prediction shows that dynamic relational structures can shape customer behavior, confirming that behavior is not always static or independent [19]. Adaptive consumer-dynamics modeling links consumer movement to hidden Markov structures and supports interpreting customer behavior as an evolving stochastic process [20]. Probabilistic path-based churn modeling provides additional evidence that customer decline and retention can be studied as sequential movement rather than as a single final label [21]. Markov-chain applications in urban land-use change demonstrate the wider usefulness of transition structures for long-run movement in dynamic systems [22]. Deep-learning-based e-commerce churn research provides a predictive benchmark for digital commerce while also motivating transparent alternatives that can explain transition pathways [23].

Studies on digital journeys, profit-driven churn, segmentation, and imbalance complete the foundation for the proposed framework. Markov-chain analysis of news user journeys shows that transition matrices can reveal behavioral movement patterns in digital environments [24]. Profit-driven churn prediction connects customer-state forecasting with managerial profitability and supports decision-oriented retention modeling [25]. B2C e-commerce churn prediction using clustering and classification confirms the link between segmentation and future-state prediction [26]. Comparative research on class-imbalance techniques shows that state-frequency differences must be interpreted carefully when rare favorable states are modeled [27]. Taken together, the reviewed studies show that transaction histories can be transformed into meaningful behavioral states, that churn and loyalty are dynamic rather than fixed conditions, and that Markov-chain transition matrices provide an interpretable way to estimate persistence, lapse, reactivation, and long-run stability. The present study builds on this foundation by applying a first-order Markov-chain framework to a large online retail customer-month panel, validating one-step prediction on a temporal holdout period, and interpreting the stationary distribution as an indicator of structural retention pressure.

Table 1. Literature-review evidence matrix for Markov-chain and customer-state prediction studies.

Study	Application	Main contribution	Relevance to this study
Ascarza (2018) [1]	Retention targeting	Showed that high-risk targeting may be ineffective	Warns against using risk states without transition insight
Ascarza et al. (2018) [2]	Retention management review	Synthesized retention management research	Frames managerial relevance of state transitions
Baghla and Gupta (2022) [3]	E-commerce churn	Evaluated classification techniques for churn	Supports comparison with predictive alternatives
Burez and Van den Poel (2009) [4]	Class imbalance in churn	Examined imbalance handling in churn prediction	Motivates evaluation beyond majority states
Chen (2012) [5]	Online Retail II dataset	Sequential transactional data source for retail behavior modeling	Supports longitudinal state construction
Chen, Sain, and Guo (2012) [6]	Online retail RFM segmentation	Used transaction histories for customer segmentation	Shows suitability of online retail data for customer analytics
Coussement and Van den Poel (2008) [7]	Churn prediction	Applied support vector machines to subscription churn	Shows classification strengths and interpretability limits
Dinh, Nguyen, and Bui (2022) [8]	Brand switching	Used Markov chains for switching behavior	Supports transition probability interpretation

Study	Application	Main contribution	Relevance to this study
Fader and Hardie (2009) [9]	Customer-base probability models	Reviewed probability models for customer-base analysis	Positions probabilistic modeling in non-contractual settings
Fader, Hardie, and Lee (2005) [10]	RFM and customer lifetime value	Linked recency-frequency-monetary evidence with future value	Supports behavioral-state features
Grunt et al. (2017) [11]	Markov decision process	Modeled customer behavior as decision process states	Direct methodological connection to Markov states
Gupta et al. (2006) [12]	Customer lifetime value	Reviewed CLV and customer-equity modeling	Connects behavioral states with managerial value
Hadden et al. (2007) [13]	Churn management review	Reviewed data-mining approaches for churn	Motivates retention-state prediction
Harish and Malathy (2023) [14]	Retail segment prediction	Combined K-means with Markov modeling	Closest retail-state transition comparator
Huang, Kechadi, and Buckley (2012) [15]	Telecom churn	Applied data mining to churn prediction	Provides comparative predictive context
Jandera and Skovranek (2022) [16]	Hidden Markov e-commerce	Developed a hidden Markov model for customer behavior	Strong direct precedent for e-commerce Markov modeling
Jerath, Fader, and Hardie (2016) [17]	Customer-base summary data	Modeled customer-base behavior from repeated summaries	Supports dynamic customer-base inference
Keramati et al. (2014) [18]	Telecom churn	Improved churn prediction using data mining	Supports temporal customer-risk analysis
Kim, Jun, and Lee (2014) [19]	Telecom churn networks	Used large-network information for churn prediction	Shows that behavior is relational and dynamic
Liberati et al. (2022) [20]	Consumer dynamics	Modeled adaptive consumer dynamics	Supports behavioral movement perspective
Mitrović and De Weerd (2020) [21]	Probabilistic churn paths	Modeled churn with probabilistic meta-path representations	Shows sequential/path-based customer modeling
Okwuashi and Ndehedehe (2021) [22]	Land-use change	Integrated machine learning with Markov chains	Shows Markov chains in spatial dynamic systems
Pondel et al. (2021) [23]	E-commerce churn	Applied deep learning to e-commerce churn support	Provides predictive benchmark context
Vermeer and Trilling (2020) [24]	News user journeys	Applied Markov chains to digital journey behavior	Demonstrates transition modeling in user behavior
Verbeke et al. (2012) [25]	Profit-driven churn prediction	Connected churn prediction to managerial profitability	Supports decision-oriented retention modeling
Xiahou and Harada (2022) [26]	B2C e-commerce churn	Combined clustering and classification for churn	Supports state-segmentation and prediction link
Zhu, Baesens, and vanden Broucke (2017) [27]	Churn imbalance	Compared imbalance techniques in churn prediction	Motivates careful state-frequency interpretation

This table positions the reviewed studies by application, main contribution, and relevance to the present transition-based customer behavior framework.

III. RESEARCH AIM AND QUESTIONS

This study aims to develop and empirically validate a Markov chain-based framework for predicting dynamic customer behavior through transition probability modeling. The study uses observed monthly customer-state movements to estimate one-step transition probabilities, long-run steady-state behavior, and predictive performance on future customer-month observations.

The study is guided by three research questions.

First, how can online retail customer behavior be represented as a finite sequence of discrete states suitable for Markov-chain modeling?

Second, what do the estimated transition probability matrices reveal about short-term movement, persistence, reactivation, and loyalty instability?

Third, how accurately can a first-order Markov chain predict future customer states compared with a simple state-persistence baseline?

IV. RESEARCH GAP

Existing customer-behavior studies often emphasize churn classification, customer segmentation, or lifetime-value prediction. These approaches are valuable, but they frequently treat the customer as a static observation at a selected time point. Less attention is given to the transition mechanism through which customers move among inactivity, risk, occasional purchasing, active purchasing, and loyalty. This study addresses the need for a transparent, transition-based framework that converts transaction histories into probabilistic state movement, long-run stability indicators, and interpretable future-state forecasts.

V. STUDY CONTRIBUTION

This study contributes a transparent Markov-chain framework for modeling dynamic customer behavior across inactive, at-risk, occasional, active, and loyal states. It converts transaction histories into a customer-month panel, estimates one-step and multi-step transition probabilities, and derives the long-run stationary distribution.

Empirically, the framework is validated using 805,549 cleaned transactions from 5,878 customers, producing 92,679 consecutive customer-month transitions. The findings quantify persistence, lapse, reactivation, and loyalty movement, showing strong stability in inactivity and greater instability in favorable purchasing states.

From a decision-support perspective, the framework identifies the at-risk state as a key intervention point and reveals long-term retention pressure. The approach is also transferable to other dynamic systems represented by discrete states, including disease progression, machine reliability, education, weather, and financial behavior.

VI. PROPOSED METHOD

The proposed method follows a conservative empirical design. The customer is the unit of analysis, the month is the transition interval, and the behavioral state is derived from purchasing activity and recent inactivity. The method is intentionally interpretable: each transition probability can be traced back to observed movements in the customer-month panel.

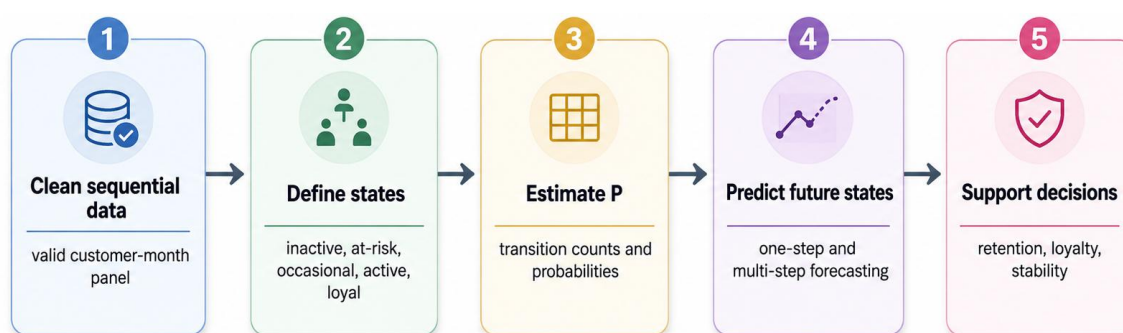


FIGURE 1. Proposed Markov chain-based prediction framework.

The diagram shows how cleaned transaction records are converted into customer states, transition probabilities, future-state predictions, and decision-support outputs.

1. MATHEMATICAL SPECIFICATION

Let X_t denote the state a customer occupies during month t . A first-order discrete-time Markov chain assumes that the next state depends on the current state rather than on the full observed history:

$$P(X_{t+1} = j \mid X_t = i, X_{t-1}, \dots, X_0) = P(X_{t+1} = j \mid X_t = i) \quad (1)$$

The one-step transition probability from state i to state j is estimated from observed transition counts:

$$p_{ij} = \frac{n_{ij}}{\sum_k n_{ik}}, \quad 0 \leq p_{ij} \leq 1, \quad \sum_j p_{ij} = 1 \quad (2)$$

The transition matrix P contains all one-step transition probabilities:

$$P = [p_{ij}], \quad i, j \in \{Inactive, At-risk, Occasional, Active, Loyal\} \quad (3)$$

Multi-step future-state probabilities are obtained by matrix exponentiation:

$$\pi_{t+h} = \pi_t P^h \quad (4)$$

The long-run steady-state distribution is estimated from the stationary condition:

$$\pi = \pi P, \quad \sum_i \pi_i = 1 \quad (5)$$

One-step prediction accuracy is calculated as follows:

$$Accuracy = \frac{1}{N} \sum_{r=1}^N I(\hat{y}_r = y_r) \quad (6)$$

VII. METHODOLOGY

1. RESEARCH DESIGN

The study uses a secondary quantitative empirical design. The analysis transforms historical online retail transactions into a customer-month panel and estimates transition probabilities among behavioral states. The design is predictive and explanatory: it forecasts future states while also identifying state persistence, instability, and reactivation patterns.

2. DATA SOURCE AND SAMPLE CONSTRUCTION

The empirical data consist of two years of transactions from a United Kingdom-based online retailer. The data include invoice identifiers, product codes, product descriptions, quantities, invoice dates, unit prices, customer identifiers, and country information. We excluded observations without valid customer identifiers, non-positive quantities, non-positive prices, and cancellation records to focus on completed, positive purchase behavior.

Table 2. Data source and cleaned analytical sample.

Item	Value
Original transaction rows	1,067,371
Columns	8
Observation period	December 2009 to December 2011
Valid purchase rows after cleaning	805,549
Customers retained for analysis	5,878
Monthly periods	25
Customer-month panel rows	98,557
Consecutive state transitions	92,679

This table defines the cleaned analytical sample used to build the customer-month panel and estimate Markov transition probabilities.

3. STATE DEFINITION

Customer behavior was represented using five states. Inactive refers to a customer-month with no purchase after at least three months since the last purchase. At-risk refers to a customer-month with no

purchase but with a purchase during the previous one or two months. Occasional refers to exactly one invoice in the month. Active refers to two or three invoices in the month. Loyal refers to four or more invoices in the month. This state design preserves interpretability and allows modeling of both inactive and active behavioral movement.

Table 3. Customer-state operational definitions.

State	Operational definition
Inactive	No purchase in current month and at least three months since previous purchase
At-risk	No purchase in current month but a purchase occurred within previous one or two months
Occasional	Exactly one invoice in the month
Active	Two or three invoices in the month
Loyal	Four or more invoices in the month

These definitions ensure that each customer-month is assigned to one interpretable behavioral state before transition probabilities are estimated.

4. ANALYTICAL PROCEDURE

The procedure consisted of six steps. First, transaction records were cleaned and converted into monthly customer-level observations. Second, customer states were assigned based on invoice frequency and recent inactivity. Third, we extracted consecutive monthly transitions for each customer. Fourth, transition counts were converted into transition probabilities. Fifth, we estimated the stationary distribution to examine long-run system behavior. Sixth, we conducted temporal holdout validation by estimating the transition matrix on earlier months and testing one-step predictions on later months.

VIII. RESULTS

1. OBSERVED CUSTOMER-STATE DISTRIBUTION

The observed customer-month distribution is dominated by inactive and at-risk states. Inactive customer-months account for 47.72% of the panel, while at-risk customer-months account for 26.31%. Occasional purchasing accounts for 19.63%, active purchasing for 5.38%, and loyal purchasing for only 0.96%. This confirms that loyalty is rare and that much of the system is concentrated in non-purchase or low-purchase states.

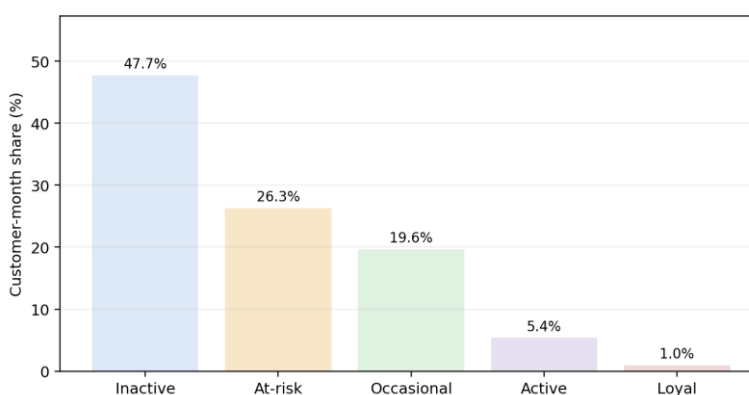


FIGURE 2. Observed customer-state distribution.

The chart shows that non-purchase and low-purchase states dominate the panel, indicating a highly imbalanced behavioral system.

Table 4. State-level descriptive statistics.

State	Customer-months	Customers represented	Mean invoices	Mean monthly revenue
Inactive	47,036	4,800	0.00	0.00
At-risk	25,926	5,749	0.00	0.00
Occasional	19,344	5,671	1.00	430.61
Active	5,304	2,150	2.23	971.75
Loyal	947	307	6.14	4497.83

The table links each behavioral state with customer coverage, purchase frequency, and average monthly revenue, confirming that loyalty is rare but high-value.

2. TRANSITION PROBABILITY MATRIX

The estimated one-step transition matrix shows strong persistence in inactivity and moderate persistence in loyalty. Customers in the inactive state remain inactive in 90.2% of the next monthly observations. At-risk customers remain at-risk in 43.0% of transitions and become inactive in 31.7%, showing a clear pathway from short-term lapse to deeper inactivity. Occasional customers are most likely to become at-risk in the next month, while active customers are also likely to lapse into at-risk status. Loyal customers show the strongest positive persistence among active states, remaining loyal in 44.6% of transitions and moving to active status in 25.1%.

Table 5. One-step Markov transition probability matrix.

Current state	Inactive	At-risk	Occasional	Active	Loyal
Inactive	0.902	0.000	0.086	0.012	0.001
At-risk	0.317	0.430	0.200	0.049	0.003
Occasional	0.000	0.692	0.226	0.075	0.007
Active	0.000	0.465	0.275	0.218	0.042
Loyal	0.000	0.162	0.141	0.251	0.446

The matrix reports the probability that a customer in each current state moves to each possible next state during the following month.

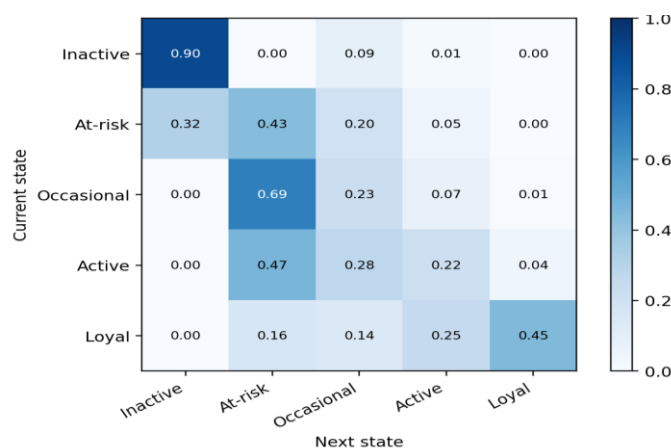


FIGURE 3. Heatmap of the one-step transition probability matrix.

The heatmap visualizes the same transition matrix, making the strongest persistence and lapse pathways easier to identify.

3. LONG-RUN STEADY-STATE BEHAVIOR

The stationary distribution indicates that, if the observed transition process continues without strategic intervention, the system tends toward a high inactive-state share. The estimated long-run state probabilities are 62.89% inactive, 19.44% at-risk, 13.41% occasional, 3.66% active, and 0.60% loyal. This result is important because it shows that the transition structure is not only descriptive but also diagnostic: current movement patterns imply an unfavorable long-run balance unless reactivation or retention mechanisms alter transition probabilities.

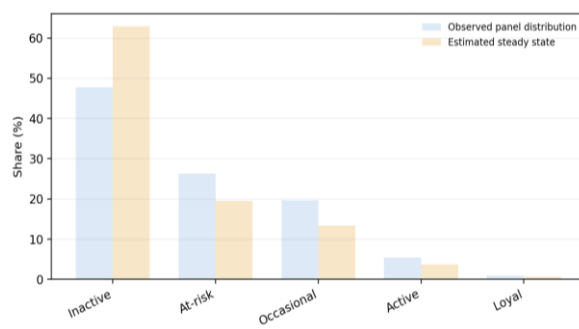


FIGURE 4. Observed distribution and long-run steady-state estimate.

The chart compares the observed panel distribution with the estimated long-run state distribution implied by the transition matrix.

4. PREDICTIVE VALIDATION

Temporal validation used earlier transitions to estimate the model and later transitions for one-step prediction. The Markov model achieved 75.59% accuracy on the holdout period, compared with 66.32% for a simple persistence baseline that predicts the next state to be the same as the current state. The smoothed probabilistic log loss was 0.642, substantially below the uniform five-state benchmark of 1.609. These results indicate that the transition matrix captures meaningful dynamic information beyond simple state persistence.

Table 6. Holdout predictive validation results.

Metric	Result
Training transitions	65,340
Holdout transitions	27,339
Markov one-step accuracy	75.59%
Persistence baseline accuracy	66.32%
Smoothed Markov log loss	0.642
Uniform five-state log loss	1.609

The validation results show that the Markov model improves one-step prediction relative to a simple persistence baseline.

Table 7. Holdout prediction accuracy by current state.

Current state	Class-level accuracy	Holdout state count
Inactive	91.28%	15,869
At-risk	42.95%	5,292
Occasional	69.03%	4,621
Active	48.13%	1,338
Loyal	33.33%	219

The class-level results indicate that prediction is strongest for inactive customers and weaker for rare loyal-state observations.

IX. DISCUSSION

The results show that Markov chains provide a clear and empirically useful framework for predicting dynamic customer behavior. The most important result is the asymmetry of transition movement. Positive states are more fragile than negative states. Inactive behavior is highly persistent, while occasional and active purchasing often lapse into at-risk status in the next monthly period. This pattern suggests that customer inactivity is not simply a temporary absence of purchases; it behaves as a structurally stable state in the observed system.

The at-risk state is especially important. It is a short-term non-purchase condition, but it has a strong probability of remaining at-risk or deteriorating into inactivity. This makes it a useful early-warning state. From a managerial perspective, the at-risk category is more actionable than the inactive category because customers in this state have recently purchased and may still be responsive to timely intervention. From a methodological perspective, this demonstrates the value of separating recent inactivity from deeper inactivity rather than treating all non-purchase periods as the same state.

The loyal state also provides useful insight. Loyal customers have the highest probability of remaining in a favorable state, yet loyalty is not permanent. A substantial share of loyal customer-months shifts downward to active, occasional, or at-risk states. This means that loyalty should be interpreted as a probabilistic condition rather than a fixed customer identity. Markov chains are well suited to this interpretation because they represent loyalty as a state with estimated probabilities of persistence and decline.

The steady-state distribution strengthens the interpretation of structural retention risk. The estimated stationary distribution indicates that the system tends toward a high inactive share if transition behavior remains unchanged. This finding should not be interpreted as a deterministic forecast of business failure. Rather, it shows what the transition structure implies under stable probabilities. If a firm improves reactivation campaigns, loyalty programs, or customer experience, then the transition matrix itself may change. Therefore, the Markov model can be used as a monitoring tool: managers can compare transition matrices before and after interventions to determine whether customer movement has improved.

The validation results confirm the model's predictive value. The Markov model outperformed a persistence baseline, which is important because customer-state data can be dominated by repeated inactive states. A model that predicts no change may appear strong in imbalanced systems. The improvement over persistence indicates that the estimated transition probabilities capture additional information about likely movement. However, the lower accuracy for rare states such as loyal status also shows that rare-state prediction remains challenging and should be handled carefully in future extensions.

X. PRACTICAL IMPLICATIONS

For practitioners, the framework provides a compact dashboard for customer movement. Managers can use the transition matrix to identify which states require intervention, which transitions to encourage, and which negative movements to reduce. At-risk customers may be prioritized for retention actions because they are more recently engaged than fully inactive customers. Loyal customers may require maintenance strategies because loyalty persistence is meaningful but not guaranteed. The framework can also be re-estimated across time periods, countries, product categories, or campaign windows to evaluate whether interventions change behavioral movement.

XI. LIMITATIONS AND FUTURE RESEARCH

The study has limitations. First, the model uses a first-order Markov assumption, meaning the next state depends only on the current state. Some customer behaviors may depend on longer histories. Second, the monthly interval is useful for interpretability but may hide shorter purchase cycles. Third, the state

definitions are deliberately simple and based on invoice frequency and recency. Future research could compare alternative state definitions based on monetary value, product diversity, or customer tenure. Fourth, rare loyal-state observations reduce predictive stability for loyalty transitions. Future studies may extend the framework using higher-order Markov chains, hidden Markov models, covariate-dependent transition matrices, Bayesian smoothing, or intervention-based transition analysis.

XII. CONCLUSION

This study developed and empirically validated a Markov chain-based framework for predicting dynamic customer behavior. Using a two-year online retail transaction dataset, the analysis transformed customer histories into monthly behavioral states and estimated transition probabilities across inactivity, risk, occasional purchasing, active purchasing, and loyalty. The findings show that inactivity is highly persistent, at-risk behavior is a critical early-warning condition, and favorable purchasing states are less stable than negative states. The long-run stationary distribution indicates that the observed transition structure tends toward a high inactive-state share, revealing structural retention pressure. Predictive validation further shows that the Markov model outperforms a simple persistence baseline, confirming that transition probabilities contain useful forecasting information. Overall, the study demonstrates that Markov chains are not only mathematically suitable for dynamic systems but also practically useful for decision support. Their main strength is interpretability: researchers and managers can directly observe how states evolve and where interventions may be most effective. The proposed framework can be transferred to other dynamic systems where repeated observations can be represented as discrete state transitions.

Author Contributions

The author conducted the conceptualization, methodology, data analysis, investigation, writing, review, editing, and final approval of the manuscript.

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Data Availability

The dataset will be available from the author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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