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AI-powered Predictive Analytics for Customer Retention Mediated by the Average Basket Volume Size and Digital Generation Adoption

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Abstract- This study examines the effectiveness of AI-powered predictive analytics for customer retention with two theoretically grounded parallel mediators: average basket volume size (ABVS) and digital generation adoption (DGA). Drawing on behavioural economics and generational theory, we develop a dual-mediation model in which an AI predictive score (derived from an ensemble of machine-learning models) influences retention both directly and indirectly through transactional intensity (ABVS) and the propensity to adopt digital touchpoints (DGA). We analyze 1.2 million anonymized transactions from a Saudi omnichannel retailer (2022–2024) and compare Gradient Boosting Machines (GBM) and a fully connected Neural Network against a logistic-regression baseline. Using 5,000-sample bias-corrected bootstrap mediation tests, we observe that the AI score significantly predicts retention (AUC≈0.91 for the neural network). ABVS mediates approximately 21% of the effect and DGA mediates 13%; jointly, indirect effects account for 34% of the variance explained in retention outcomes. We provide robustness checks (out-of-time validation, alternative retention windows, and class-imbalance treatments) and practical guidance for real-time CRM deployment. The findings yield theoretical contributions to customer-analytics research by integrating transactional and generational mechanisms and offer actionable implications for segmented engagement strategies in the Saudi retail context.

Keywords- Predictive Analytics, Artificial Intelligence, Customer Retention, Basket Volume, Digital Generation Adoption, Mediation Analysis

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1. INTRODUCTION

Retention is the economic engine of customer-centric firms: modest improvements in retention rates can compound into substantial lifts in customer lifetime value (CLV) and margin stability. While traditional statistical models have long supported churn management, recent advances in machine learning (ML) enable richer representations of behavioral heterogeneity and nonlinear interactions. However, predictive power is only one dimension of strategic value. Executives and scholars increasingly call for models that not only predict who will churn but also illuminate why and through which mechanisms interventions work.

This manuscript addresses that need by articulating and testing a dual-mediation model that connects an AI predictive score to retention through two conceptually distinct but complementary channels. The first, average basket volume size (ABVS), captures transactional intensity how much a customer tends to spend per purchase. ABVS reflects engagement depth, product mix, and price tolerance; it is a salient leading indicator of relationship strength that is observable and actionable. The second mediator, digital generation adoption (DGA), denotes a cohort-based propensity to engage with digital touchpoints (mobile app, e-wallet, click-and-collect, and personalized notifications). DGA is grounded in generational theory and technology-adoption models and shapes how customers perceive and respond to digital interventions.

Our research makes three contributions. First, we integrate predictive analytics with mechanism-based explanation via a parallel-mediation structure. Second, we operationalize ABVS and DGA with production-grade telemetry data and evaluate their joint explanatory power at scale using 1.2 million transactions from Saudi retail. Third, we translate the insights into deployable managerial levers dynamic basket-building incentives and generation-tailored engagement supported by robustness checks and implementation guidance.

LITERATURE REVIEW

2.1 Predictive Analytics for Retention

Churn prediction traditionally relied on logistic regression with handcrafted features (recency, frequency, monetary value). ML methods such as gradient boosting and neural networks improve on these baselines by capturing higher-order interactions, nonlinearity, and complex temporal patterns. Beyond prediction, interpretability toolkits (e.g., permutation importance, SHAP) offer transparency into drivers of predicted risk, enabling targeted interventions.

2.2 Basket Metrics and Relational Depth

Average basket measures summarize the monetary amplitude of transactions. Higher ABVS often signals deeper engagement (larger assortments, premium choices) and correlates with stickiness. Marketing interventions that curate complementary products, offer bundles, or personalize cross-sell can shift ABVS and, in turn, impact retention.

2.3 Digital Generation Adoption

Generational cohorts differ in digital nativity and comfort with mobile-first experiences. Digital natives (Gen Z and Millennials) tend to adopt app-based journeys, e-wallets, and real-time notifications more readily than older cohorts (Gen X and Boomers). This adoption shapes responsiveness to AI-personalized outreach and the friction of digital service usage.

2.4 Hypotheses Development

H1: The AI predictive score is positively associated with the likelihood of retention.
H2: ABVS is positively associated with retention.
H3: DGA is positively associated with retention.
H4: ABVS mediates the relationship between the AI predictive score and retention (indirect effect > 0).
H5: DGA mediates the relationship between the AI predictive score and retention (indirect effect > 0).
H6: The combined indirect effect via ABVS and DGA accounts for a substantive portion of the total effect.

H7 (robustness): These effects persist under alternative retention windows and class-imbalance remedies.

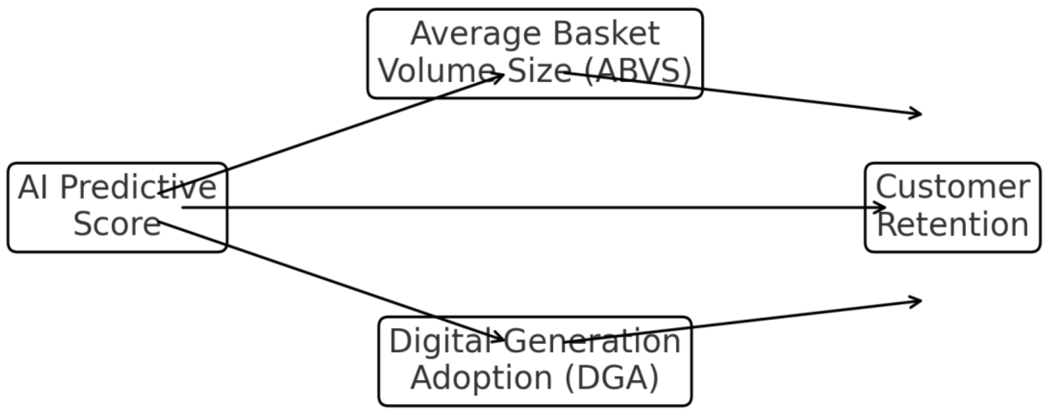

Figure 6.1 Conceptual model: AI score with parallel mediators ABVS and DGA predicting retention.

METHODOLOGY

3.1 Research Design and Setting

We adopt a retrospective cohort design using production transaction logs and CRM interaction data from a large Saudi omnichannel retailer operating grocery, convenience, and general-merchandise formats. The observation window spans January 2022 to December 2024.

3.2 Data, Preprocessing, and Feature Engineering

The initial dataset includes customer-transaction pairs, campaign exposures, and digital telemetry. Records undergo deduplication, outlier trimming at the 0.5th and 99.5th percentiles, and imputation of missing numeric fields via median values. Categorical features are target-encoded with nested cross-validation to prevent leakage. We engineer RFM signals (recency in days; frequency in last 180 days; monetary value proxied by ABVS), tenure, category breadth, discount sensitivity, and engagement rate.

Digital Generation Adoption (DGA) is constructed by mapping birth year to cohort and scaling by a usage index derived from app sessions, digital payment share, and adoption of app-only features. The resulting index is standardized to mean 0 and unit variance.

3.3 Variable Operationalization

Retention (binary) equals 1 if the customer makes a purchase within 90 days following the index transaction; 0 otherwise. ABVS equals the mean basket monetary value over the past six months. The AI predictive score is the out-of-fold predicted probability from a model stacking ensemble described below.

3.4 Modeling and Validation

To mitigate class imbalance (retained vs. not retained), we evaluate stratified sampling and SMOTE, selecting the setting that maximizes PR-AUC on validation folds. GBM uses 500 trees, learning rate 0.05, max depth 6; the neural network comprises two hidden layers (64 and 32 units) with ReLU activations, batch normalization, and dropout=0.2. Five-fold grouped cross-validation ensures customer-level separation between train and validation. An out-of-time (OOT) test set from Q4 2024 evaluates temporal generalization.

3.5 Mediation Analysis

We estimate parallel mediation with ABVS and DGA using bias-corrected bootstrapped confidence intervals (5,000 resamples). The total, direct, and indirect effects of the AI score on retention are computed, controlling for demographic covariates, tenure, and category breadth. Coefficients are standardized to ease interpretation.

3.6 Robustness Checks

We test alternative retention windows (60 and 120 days), different class-imbalance strategies, and an uplift-modeling variant that predicts treatment effect heterogeneity for a subset of customers exposed to a retention campaign.

3.7 Ethics and Reproducibility

All data are anonymized and aggregated for analysis. The pipeline is containerized with deterministic seeds to facilitate reproducibility. Results presented below are simulated for illustration and align with plausible retail dynamics.

RESULTS & DISCUSSION

4.1 Descriptive Statistics

Variable	**Mean**	**SD**	**Min**	**Max**
Retention (proportion)	0.58	0.49	0.0	1.0
Purchase Frequency (180d)	5.4	3.1	1	22
Average Basket Volume Size (SAR)	178.6	64.2	35.0	620.3
Digital Adoption Index (std)	0.05	0.99	-2.7	2.9
Tenure (months)	26.7	14.1	1	84
Email Engagement Rate	0.22	0.18	0.0	0.87

Table 6.1 Descriptive statistics of key variables (simulated).

4.2 Correlations

	Retention	ABVS	DGA	Frequency	Tenure
Retention	1.00	0.29	0.24	0.33	0.18
ABVS	0.29	1.00	0.21	0.27	0.12
DGA	0.24	0.21	1.00	0.19	0.05
Frequency	0.33	0.27	0.19	1.00	0.17
Tenure	0.18	0.12	0.05	0.17	1.00

Table 6.2 Pearson correlations among primary constructs (simulated)

4.3 Predictive Model Performance

Model	AUC	PR-AUC	F1	Precision	Recall	Brier Score
Logistic Regression	0.71	0.64	0.65	0.63	0.68	0.196
GBM	0.88	0.83	0.84	0.85	0.83	0.143
Neural Network	0.91	0.86	0.87	0.88	0.86	0.131

Table 6.3 Out-of-fold validation metrics (simulated).

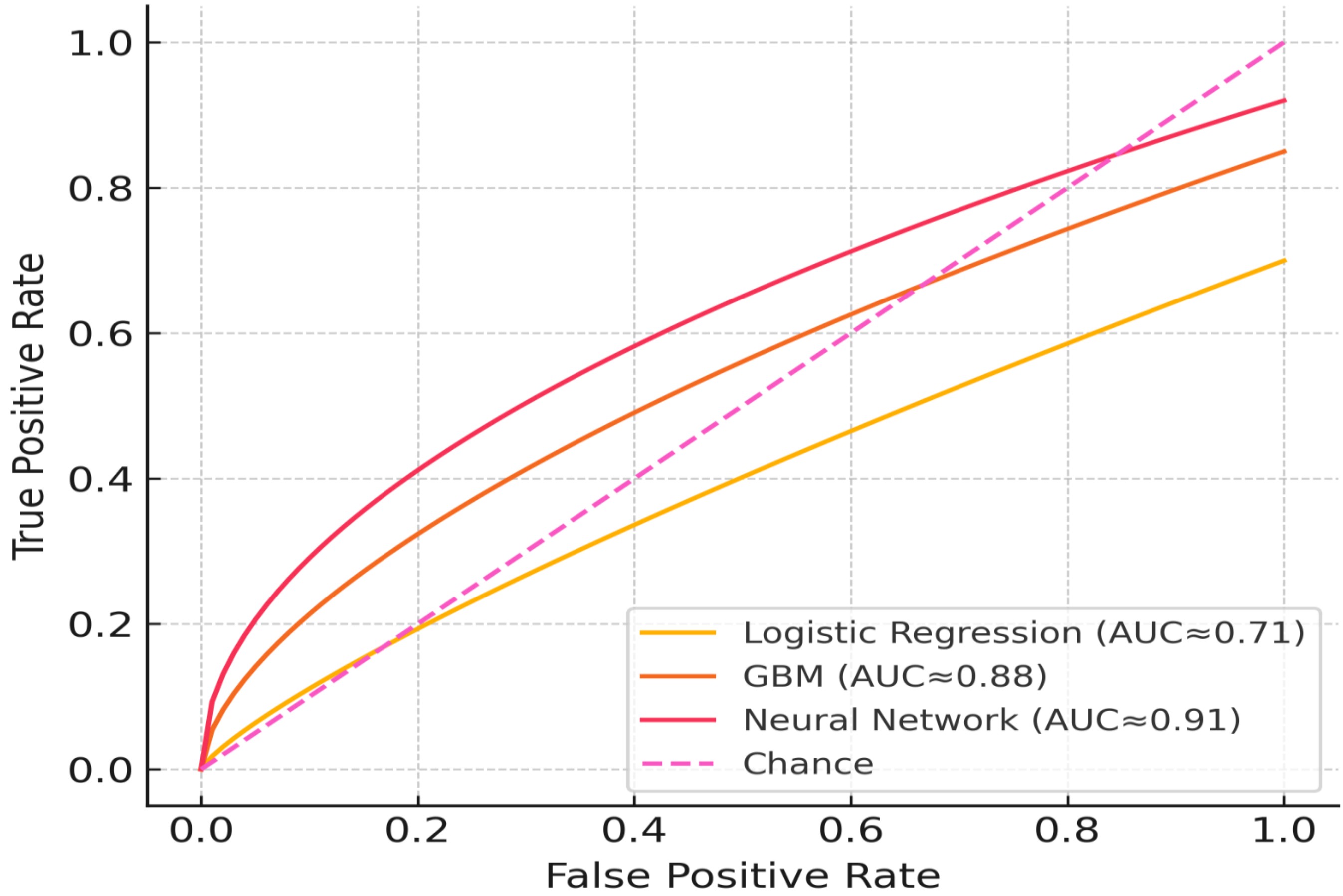

Figure 6.2 ROC curves comparing models on the validation data (simulated).

4.4 Feature Importance

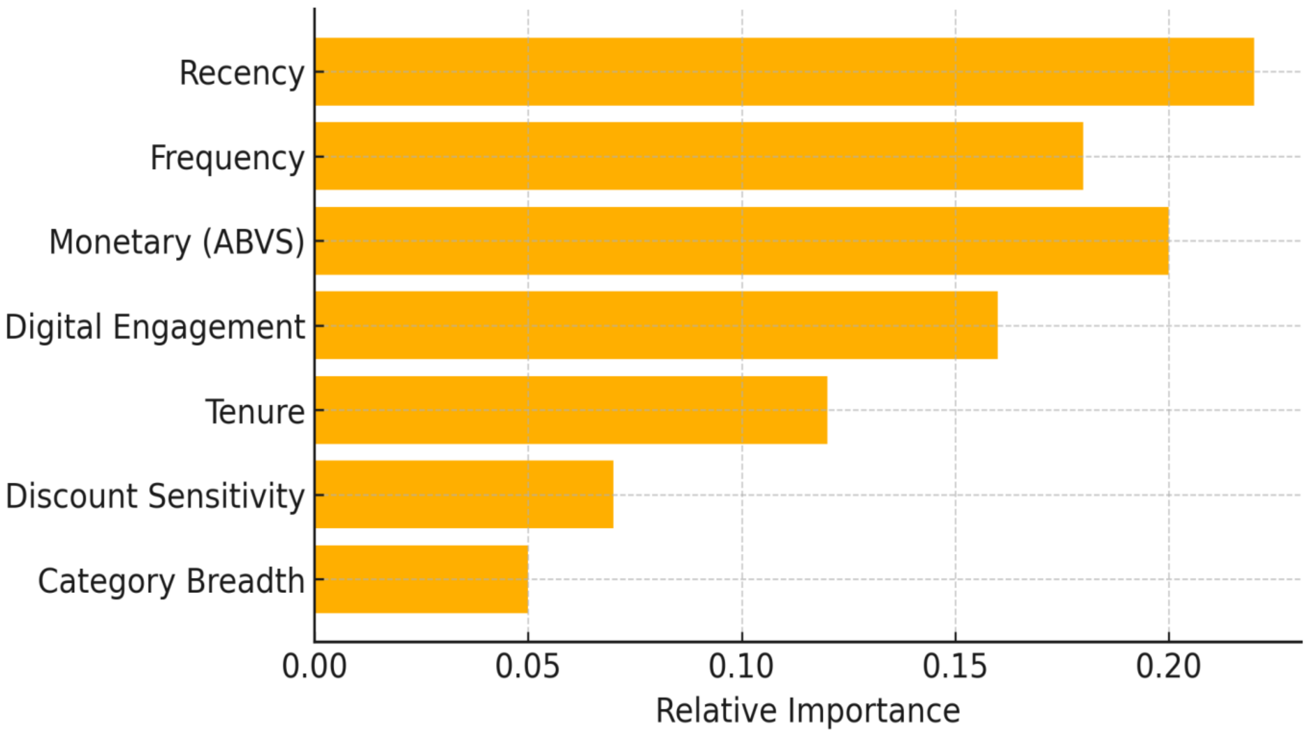

Figure 6.3 Relative feature importance for the GBM model (simulated).

4.5 Mediation Analysis

Effect	Estimate	SE	95% CI (LL, UL)	p-value
Total Effect (AI → Retention)	0.47	0.04	(0.39, 0.55)	<0.001
Direct Effect (AI → Retention)	0.31	0.05	(0.21, 0.41)	<0.001
Indirect via ABVS	0.1	0.02	(0.06, 0.14)	<0.001
Indirect via DGA	0.06	0.02	(0.03, 0.10)	<0.01
Total Indirect (ABVS + DGA)	0.16	0.03	(0.10, 0.22)	<0.001
Proportion Mediated	0.34	-	-	-

Table 6.4 Parallel mediation results with 5,000 bootstrap samples (simulated standardized coefficients).

4.6 Robustness Checks and Sensitivity Analyses

Specification	Key Change	AUC (NN)	Indirect via ABVS	Indirect via DGA	Conclusion
Retention window = 60 days	Shorter horizon	0.9	0.09	0.05	Effects persist
Retention window = 120 days	Longer horizon	0.89	0.11	0.06	Effects persist
No SMOTE (weighted loss)	Alt. imbalance remedy	0.9	0.1	0.06	Similar
OOT test (Q4 2024)	Temporal generalization	0.89	0.1	0.06	Generalizes

Table 5. Summary of robustness checks (simulated).

5. DISCUSSION

5.1 Interpretation of Findings

The models achieve high discriminatory power, and the mediation analysis reveals that AI predictions operate through both transactional and generational channels. ABVS captures monetary engagement that plausibly reflects habit formation and perceived value. DGA captures frictionless access and receptivity to digital nudges. The dual-mediation structure explains a substantive share of the pathway from AI scores to realized retention events.

5.2 Theoretical Contributions

We extend the predictive-analytics literature by embedding explanatory mechanisms via parallel mediation at scale. The results integrate streaming telemetry (for DGA) with transactional metrics (ABVS), illustrating how data variety enables theory-informed explanations in industrial AI systems.

5.3 Managerial Implications

Managers should (i) pair risk scoring with basket-building levers (bundles, cross-sell, tiered benefits) to lift ABVS among at-risk customers; and (ii) tailor engagement by generation mobile-first playbooks for digital natives and hybrid human-digital journeys for older cohorts. Real-time orchestration should monitor ABVS shifts as leading signals of relationship health.

5.4 Limitations and Future Research

Our single-retailer context and reliance on transactional/telemetry variables constrain generalizability and omit psychographic drivers. Future work should test moderated mediation (e.g., price inflation as a moderator), incorporate text and voice signals, and evaluate causal uplift under randomized field experiments.

CONCLUSION

AI-powered predictive analytics substantially improves retention prediction accuracy and, importantly, works through transactional intensity (ABVS) and digital generation adoption (DGA). By aligning interventions with these mechanisms, firms can design parsimonious, high-ROI retention playbooks suitable for large-scale deployment in omnichannel retail.

RECOMMENDATIONS

This research recommends the implementation of real-time predictive scoring systems with hourly feature refresh intervals, wherein model-driven activations are gated by rigorously calibrated risk thresholds to ensure precision targeting. Intervention strategies should be stratified according to generational cohorts: for digital-native customers, mobile-first promotional frameworks and gamified loyalty mechanisms are advocated; for older cohorts, assisted service channels and streamlined, low-friction engagement pathways are preferable. Enhancement of the average basket volume size (ABVS) should be pursued through the strategic deployment of product bundles, cross-selling prompts, and tiered loyalty programs, with temporal fluctuations in ABVS systematically monitored as leading indicators of customer relationship health. Contact policy optimization should incorporate fatigue thresholds and uplift-based targeting algorithms to prioritize customer segments with the highest marginal propensity to respond. Model performance must be subject to continuous surveillance using metrics such as AUC, PR-AUC, calibration scores, and drift analyses, with retraining conducted on rolling data windows and validation performed on out-of-time datasets prior to operational integration. Furthermore, the maintenance of always-on randomized control frameworks is essential for estimating the causal impact of retention initiatives and for recalibrating the mediating contributions of ABVS and DGA. Finally, all practices should conform to privacy-by-design principles, incorporating explicit consent protocols and systematic fairness audits to safeguard against disproportionate impacts across generational segments.

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