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A Machine Learning Model for Predicting Customer Retention and Optimizing Digital Marketing Strategies in Sports E-Commerce

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Abstract
Customer retention is one of the strongest drivers of profitability in online retail, yet many sports e-commerce businesses continue to allocate the bulk of their digital marketing budgets to acquisition rather than to keeping existing customers. This paper combines a structured literature synthesis with a predictive modelling study to develop a machine learning framework that predicts whether a sports e-commerce customer will make a repeat purchase within 180 days, and then uses those predictions to guide the allocation of retention marketing spend. The study was conducted within the product marketing function of FitandPro Sports Management Limited. The synthesis of 155 sources informs a conceptual model linking transactional, engagement, experience, relationship and channel antecedents, through an analytics and decision layer, to targeted marketing action and customer lifetime value, expressed as six propositions. Fourteen features were engineered for a cohort of 24,000 customer profiles structured on the company's customer record schema, and three classifiers were compared: logistic regression, random forest and gradient boosting. All three achieved similar discrimination on a held-out test set (area under the ROC curve between 0.765 and 0.773), with logistic regression performing marginally best while remaining fully interpretable. Purchase recency, customer satisfaction, loyalty programme membership, email engagement and product return rate were the most influential predictors. Customers in the highest predicted risk decile churned at 82.3 percent, against a base rate of 36.4 percent. A campaign simulation showed that directing a fixed retention budget to the customers ranked highest by predicted risk roughly doubled the number of customers retained compared with untargeted outreach, and that weighting risk by customer value nearly tripled the value preserved. The paper sets out theoretical and managerial implications, including a tiered retention playbook, and identifies limitations and directions for future research.

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Keywords: Customer retention, churn prediction, machine learning, digital marketing, sports e-commerce, customer lifetime value, marketing optimisation, conceptual model

1. Introduction

1.1. Background

The sports and fitness retail sector has moved rapidly online. Consumers now research, compare and purchase footwear, apparel, equipment and nutrition products through websites, mobile apps and social commerce platforms. For businesses such as FitandPro Sports Management Limited, this shift has created a large and growing base of digitally acquired customers, together with rich behavioural data describing how those customers browse, buy, return products and respond to marketing. Across Sub-Saharan Africa, this digital shift has been accelerated by wider adoption of online payment portals, digital banking,

fintech-enabled transactions and high-throughput digital collections platforms (Agboada *et al*., 2022; Agyei *et al*., 2019; Okafor *et al*., 2021; Osuji *et al*., 2021) [6, 12, 99, 114].

The economics of e-commerce make retention especially important. Reichheld and Sasser (1990) [122] showed that modest improvements in customer retention can produce disproportionately large gains in profit, because retained customers buy more over time, cost less to serve and refer others. Later work on customer lifetime value (Gupta, Lehmann and Stuart, 2004; Rust, Lemon and Zeithaml, 2004) [66, 123] formalised the idea that the value of a firm is closely tied to the value of its customer base. Studies of subscriber-based and service businesses in emerging markets reach a similar conclusion, linking retention and lifecycle management directly to revenue growth (Agyei *et al*., 2018; Oziri *et al*., 2020; Sakyi *et al*., 2022a) [11, 118, 125]. Yet in practice, digital marketing teams often measure success through acquisition metrics such as cost per click, cost per install and first-order conversion rate, and treat retention as a by-product rather than a managed outcome (Sanni *et al*., 2020a) [128].

Machine learning offers a practical way to close this gap. By learning from historical patterns, a predictive model can estimate each customer's likelihood of returning, allowing marketers to act before a customer lapses (Oziri *et al*., 2020) [118]. When those predictions are connected to campaign decisions, the marketing team can concentrate effort and budget where it is most likely to change outcomes (Atima *et al*., 2022; Basnet *et al*., 2021) [36, 42].

1.2. Problem Statement

At FitandPro, as in many sports e-commerce businesses, retention activity in 2022 was largely calendar-driven and uniform: the same promotional emails, discount codes and social retargeting were sent to broad segments regardless of each customer's likelihood of returning. This approach has three weaknesses. First, budget is spent on customers who would have returned anyway. Second, customers at genuine risk of leaving are not identified early enough for intervention to work. Third, heavy reliance on blanket discounting can train customers to wait for promotions, eroding margin without building loyalty. Similar targeting inefficiencies, revenue leakage and costs of poor quality have been documented in other service and retail settings where spending is not guided by predictive analysis (Ashore-Onisemo *et al*., 2021; Atima *et al*., 2022; Ebisi, Okoli, *et al*., 2021) [31, 36, 50]. A data-driven method for identifying at-risk customers and prioritising marketing action was therefore needed.

1.3. Objectives

The study had four objectives:

- To engineer a set of customer-level features that capture purchasing behaviour, engagement, service experience and acquisition source in a sports e-commerce setting.
- To build and compare machine learning models that predict 180-day customer retention.
- To identify the factors that most strongly influence retention and interpret them in marketing terms.
- To translate model outputs into an optimised digital marketing strategy, and to estimate the value of targeted retention campaigns relative to untargeted ones.

1.4. Research Questions

- **RQ1:** How accurately can customer retention be predicted from behavioural, transactional and channel data in sports e-commerce?
- **RQ2:** Which customer attributes are the strongest predictors of retention?
- **RQ3:** How much more effective is model-guided retention targeting than untargeted outreach under a fixed budget?

1.5. Significance of the Study

For practitioners, the study provides a reproducible workflow, from feature design to campaign targeting, that a mid-sized marketing team can implement with standard open-source tools, in line with calls for accessible decision-support analytics in small and medium-sized enterprises (Agwuna *et al*., 2022) [9]. For the wider literature, it adds evidence from the sports retail vertical and from an emerging-market context, where mobile-first shopping, uneven connectivity, delivery reliability and price sensitivity shape customer behaviour in ways that differ from the mature markets that dominate published churn research (Oteri and Chibwaye, 2022; Unamma, Okwesa, *et al*., 2018, 2021) [115, 144, 145].

1.6. Literature Synthesis

This section synthesises prior research across seven themes that together inform the conceptual model: customer retention and lifetime value; machine learning for churn prediction; marketing analytics; the translation of predictions into action; customer experience and fulfilment; data infrastructure and governance; and predictive decision-making in business.

1.6.1 Customer Retention and Customer Lifetime Value

Retention has long been recognised as a central lever of marketing performance. Reichheld and Sasser (1990) [122] argued that reducing customer defections is among the most powerful routes to profitability. Gupta, Lehmann and Stuart (2004) [66] linked customer metrics directly to firm valuation, showing that improvements in retention rate have a larger effect on customer value than comparable improvements in margin or acquisition cost. Fader, Hardie and Lee (2005) [60] demonstrated that recency, frequency and monetary value (RFM) summarise much of the information needed to forecast future purchasing, a finding that continues to inform feature design in retention models. Kumar and Reinartz (2016) [75] further emphasised that firms create enduring value by managing customers according to their future, rather than past, contribution.

More recent applied work extends these ideas to data-rich digital businesses. Oziri *et al*. (2020) [118] showed how predictive analytics can reduce churn and raise customer lifecycle value in telecommunications, and Ukadike (2022) [142] described how customer data platforms in emerging-market banking build the unified customer view that retention programmes require. CRM-based sales forecasting (Dada *et al*., 2021b) [49], relationship-based portfolio management (Ezeako *et al*., 2019) [59] and partnership ecosystems that extend value propositions beyond the core product (Agboada *et al*., 2020) [5] illustrate how firms deepen relationships with existing customers. Related studies treat retention and loyalty

as engines of growth in subscriber businesses (Agyei *et al*., 2018) [11] and in brand and portfolio development (Agyei, 2021; Sanni *et al*., 2020b) [10, 129]. Outside commerce, the same predictive logic has been applied to employee attrition and engagement (Ukadike, 2019) [141], underlining how general the problem of anticipating disengagement has become.

1.6.2 Machine Learning for Churn Prediction

Churn prediction has been studied extensively in telecommunications, banking and subscription services. Neslin *et al*. (2006) [94] compared many modelling approaches submitted to a churn modelling tournament and found that method choice materially affected predictive accuracy and that logistic regression and tree-based approaches both performed well. Lemmens and Croux (2006) [82] showed that ensemble methods such as bagging and boosting can improve churn prediction over single classification trees. Verbeke *et al*. (2012) [153] argued that churn models should be evaluated not only on statistical accuracy but on the profit they generate when used to target retention campaigns, an approach this paper follows. Ensemble methods such as random forests (Breiman, 2001) [45] and gradient boosting (Friedman, 2001; Chen and Guestrin, 2016) [47, 64] are now standard choices for tabular data, and recent benchmarking confirms that tree-based models remain highly competitive on such data (Grinsztajn, Oyallon and Varoquaux, 2022) [65]. At the same time, systematic comparisons in other fields have found that flexible machine learning methods do not always outperform well-specified logistic regression (Christodoulou *et al*., 2019) [48], so a simple baseline should always be included.

Binary classification problems closely related to churn have been studied across finance and operations. Machine learning models for credit risk and loan default prediction (Ashore-Onisemo *et al*., 2020; Mensah *et al*., 2022; Okoli, Pedro, *et al*., 2022) [30, 93, 101], credit decisioning in emerging markets (Uzondu *et al*., 2020) [151] and data-driven risk evaluation in financial institutions (Akomolafe and Agu, 2019b) [19] share the same structure: estimating the probability that an account will move into an undesirable state, then acting on the highest-risk cases first. The same approach underlies machine learning and data-mining methods for fraud detection (Atakpa and Abetoh, 2022; Unamma, Iziduh, *et al*., 2021) [33, 145], anti-money laundering (Atakpa, 2021) [32], predictive auditing (Abetoh and Atakpa, 2022; Okoli, Kinyanjui, *et al*., 2022) [1, 101], anti-corruption oversight (Ashore-Onisemo and Unamma, 2022b) [29] and cyber threat and anomaly detection (Okwesa *et al*., 2020) [104]. In public health, AI-based risk stratification and big data predictive models flag high-risk populations early (Oparah *et al*., 2022; Oparah, Ezeh, *et al*., 2021) [109, 110], and predictive compliance monitoring has been used to detect systemic risks from consumer complaints (Adeyelu, 2018) [4]. Studies of predictive maintenance in e-commerce systems (Mayo *et al*., 2021) [85], industrial process control (Adaramola *et al*., 2020) [2] and interpretable early failure prediction (Komi and Adamolekun, 2021) [74] apply the same early-warning logic to machines rather than customers. Methodological work highlights the importance of careful feature selection (Atakpa and Abolaji, 2021; Oloduowo *et al*., 2020; Raheem *et al*., 2020) [34, 105, 121], which informs the design used in this study.

1.6.3 Marketing Analytics, Segmentation and Attribution

A growing body of work examines how predictive analytics can improve the targeting and measurement of marketing. Predictive audience segmentation has been proposed to resolve targeting inefficiencies (Atima *et al*., 2022) [36], and segmentation and forecasting models have been developed to improve the effectiveness of targeted digital marketing (Basnet *et al*., 2021) [42]. Attribution has received particular attention: a systematic review documents the biases of rule-based models in multi-touch customer journeys (Sanni, Atima, *et al*., 2022) [131], and the measurement of marketing return on investment remains a persistent challenge (Sanni *et al*., 2020a) [128].

Other studies extend analytics to brand and go-to-market decisions. Data-driven brand positioning (Sanni *et al*., 2020b) [129], analytics-driven go-to-market planning (Sanni and Atima, 2021a) [126] and integrated marketing communications for subscriber growth (Agyei *et al*., 2018) [11] show how evidence can guide marketing strategy. Geomarketing and geospatial analytics support retail expansion and store location decisions (Seyi-Lande *et al*., 2020; Tonoyan *et al*., 2022a) [133, 137], and product management research from mobile network rollouts offers lessons for launching digital products in emerging markets (Sanni *et al*., 2020c) [130]. Business intelligence dashboards make these insights visible to executives (Sanni and Atima, 2021b) [127], while natural language processing allows unstructured customer records to be analysed at scale (Iziduh *et al*., 2020) [73]. Multichannel communication frameworks for improving engagement and conversion on digital platforms provide further guidance (Wikiri *et al*., 2022) [155], and comparative work on global marketing law reminds practitioners of the consumer protection limits within which data-driven targeting must operate (Anichukwueze *et al*., 2019) [25].

1.6.4 From Prediction to Marketing Action

A churn score alone does not guarantee better marketing outcomes. Ascarza (2018) [28] showed that customers with the highest churn risk are not always those most responsive to retention efforts, and recommended that firms consider the effect of the intervention, not just the risk of leaving. Interpretability also matters: marketers need to understand why a customer is at risk in order to choose the right message, channel and offer. Model-agnostic interpretation tools, such as permutation importance and SHAP values (Lundberg and Lee, 2017) [84], make it possible to explain predictions from complex models in business terms.

Turning predictions into action increasingly depends on marketing automation. Sanni, Iwuanyanwu, *et al*. (2022) proposed adaptive control models for AI-driven marketing automation, showing how automated campaigns can be kept within business and compliance limits. Because such systems make consequential decisions about customers, they also require human oversight and ongoing governance. Human-in-the-loop machine learning keeps people in control of automated recommendations (Ladapo, Dosunmu, *et al*., 2022) [76], model observability and failure localisation help teams detect when production models degrade (Ibe *et al*., 2022) [68], and automated evaluation and governance frameworks support the responsible operation of large-scale machine learning systems (Unamma *et al*., 2022) [143].

Advances in automated software quality assurance and AI-based software testing improve the reliability of the systems through which model outputs reach customers (Borah *et al*., 2022; Mbonu, Aliliele, *et al*., 2021b; Mbonu, Okeke, *et al*., 2021) [44, 88, 91].

1.6.5 Digital Marketing and Customer Experience in Sports E-Commerce

Sports e-commerce combines functional purchases, such as running shoes or gym equipment, with identity-driven purchases tied to teams, athletes and fitness communities. Digital marketing in this space typically spans paid search, social media advertising, influencer partnerships, email and owned mobile apps (Chaffey and Ellis-Chadwick, 2019) [46]. Lemon and Verhoef (2016) [83] highlighted that customer experience across the full journey, including delivery and after-sales service, shapes loyalty. In emerging markets, fulfilment speed, product authenticity and payment convenience are particularly salient parts of that experience.

Evidence from adjacent sectors supports this emphasis on experience. Customer service analytics has been positioned as a strategic driver of revenue growth (Sakyi *et al*., 2022a) [125], first-contact resolution has been linked to service quality and satisfaction (Wikiri, 2021) [154], and digital complaint-resolution systems give customers a visible channel for redress (Unamma *et al*., 2019b) [147]. Research on the creator economy shows how operational infrastructure turns individual content into a scalable brand (Anyanwu, 2021) [27], a lesson that applies to influencer and social media campaigns in sports retail. Studies of mobile health solutions demonstrate how mobile channels can sustain long-term user engagement and adherence (Oparah, Gado, *et al*., 2021) [111], data-informed digital platforms show how usage data can be fed back into product design (Orise and Niniola, 2020) [112], and offline-first design principles address the low-connectivity conditions common in many African markets (Unamma, Okwesa, *et al*., 2018) [144].

Fulfilment completes the experience. Supply chain visibility for inventory accuracy and lead times (Feboh *et al*., 2022; Nnabueze *et al*., 2021) [62, 95], real-time order visibility for lead-time compression (Ebisi, Sam-Bulya, *et al*., 2021) [51], data-driven lean supply chains in retail (Efobi *et al*., 2022b; Ike *et al*., 2022) [55, 71], resilient distribution and logistics networks (Anene, 2021; Anene and Clement, 2022) [23, 24] and infrastructure constraints on digitally booked transport (Alaka *et al*., 2022) [20] all bear on delivery speed, which this study identifies as a retention driver.

1.6.6 Data Infrastructure, Business Intelligence and Data Governance

Predictive retention models depend on reliable data pipelines. ETL design and integration patterns in CRM-centric enterprise architectures (Badmus *et al*., 2019a, 2022b) [38, 41] and disciplined development and deployment practices for CRM platforms (Badmus *et al*., 2018, 2022a) [37, 40] provide the plumbing through which customer data reaches models and campaigns. Risk-based business intelligence architectures (Mbonu, Aliliele, *et al*., 2021a) [87], scalable infrastructure for resource-constrained organisations (Ibe *et al*., 2021) [67], cloud migration best practices (Ladapo, Jooda, *et al*., 2022) [76] and machine learning approaches to cloud resource scaling and capacity planning (Ahmed *et al*., 2020; Edivri and Oteri, 2022) [13, 53] address the reliability and cost of that infrastructure, while single-source-of-truth and interoperability frameworks protect data quality (Ilodigwe and Adesemoye, 2021; Unamma *et al*., 2019a) [72, 146]. Business intelligence dashboards (Agwuna *et al*., 2022; Ogbole *et al*., 2021; Owoade *et al*., 2022) [9, 98, 116], profitability analysis in retail operations (Akin-Oluyomi *et al*., 2020) [16], cross-functional and diagnostic KPI frameworks (Ebisi *et al*., 2022; Sakyi *et al*., 2022b; Seyi-Lande *et al*., 2022) [52, 124, 134], real-time analytics dashboards (Orise and Niniola, 2022) [113] and real-time risk dashboards built on machine learning (Filani *et al*., 2022) [63] show how analytics outputs are put in front of decision-makers.

Customer analytics also raises legal and ethical obligations. Privacy-preserving data architectures for regulated analytics (Atakpa and Abolaji, 2022) [35], governance of CRM platforms in regulated environments (Badmus *et al*., 2019b) [39], privacy-centric security engineering for cloud systems (Okoruwa *et al*., 2020) [103] and data privacy governance for cross-border digital platforms (Annan, 2022) [26] describe technical safeguards. Harmonisation of data protection compliance across the GDPR, Nigeria's NDPR and United States regimes (Ominyi and Anichukwueze, 2022a) [108], together with assessments of cyber risk maturity against the NDPR (Fadero *et al*., 2021) [61], is particularly relevant to Nigerian e-commerce firms that use global marketing platforms. Broader work on legal and ethical risk modelling in data protection (Mbonu *et al*., 2018) [86], comparative data protection regulation (Mbonu *et al*., 2019) [89], data protection impact assessments (Mbonu *et al*., 2022a) [90], privacy by design (Ominyi, 2021) [107], real-time compliance pipelines (Uchechi *et al*., 2022) [140] and information governance frameworks (Peteranaba *et al*., 2022) [120] frames the governance environment in which retention models must operate.

1.6.7 Predictive Analytics for Forecasting and Business Decisions

Retention modelling sits within a wider movement toward predictive decision systems in business. Machine learning has been applied to demand forecasting and revenue projection (Tonoyan *et al*., 2021a) [135], supply chain demand forecasting (Aifuwa *et al*., 2020) [14], cash flow modelling in retail (Tonoyan *et al*., 2021b) [136], budgeting from operational and market signals (Adesuyi *et al*., 2022) [3], process and cost optimisation (Tonoyan *et al*., 2022b, 2022c) [138, 139] and financial modelling and scenario analysis under uncertainty (Unamma, 2022) [143]. Comparative reviews of predictive forecasting for resource allocation (Unamma, Ashore-Onisemo, *et al*., 2018b) [144], data-driven performance monitoring and operations management (Efobi *et al*., 2021; Ijagbemi *et al*., 2019) [54, 69] and work on executive decision systems and analytics-driven value creation (Lawal and Oduleye, 2018a, 2019b) [78, 79] reinforce the case for embedding prediction in strategy.

1.6.8 Synthesis of Themes

Table 1 integrates the seven themes, summarising what each contributes to the conceptual model and the representative sources on which it draws.

Table 1: Synthesis of literature themes and their role in the conceptual model

Theme	Synthesised insight	Role in model	Representative sources
Retention and customer lifetime value	Retention drives profit and firm value; RFM signals forecast future purchasing	Outcome; transactional antecedents	Reichheld and Sasser, 1990; Fader, Hardie and Lee, 2005; Oziri *et al*., 2020; Ukadike, 2022
Machine learning for churn and risk	Probability-of-exit models rank cases for early action; simple models often match complex ones	Analytics layer	Neslin *et al*., 2006; Christodoulou *et al*., 2019; Ashore-Onisemo *et al*., 2020; Atakpa and Abetoh, 2022; Komi and Adamolekun, 2021
Marketing analytics and attribution	Predictive segmentation and better attribution reduce wasted spend	Decision layer; channel antecedents	Atima *et al*., 2022; Basnet *et al*., 2021; Sanni *et al*., 2020a; Sanni, Atima, *et al*., 2022
Prediction to action	Automation needs interpretability, human oversight and monitoring	Decision layer; action	Ascarza, 2018; Ibe *et al*., 2022; Ladapo, Dosunmu, *et al*., 2022; Sanni, Iwuanyanwu, *et al*., 2022
Customer experience and fulfilment	Service quality, complaints handling and delivery speed shape loyalty	Experience antecedents; interventions	Lemon and Verhoef, 2016; Feboh *et al*., 2022; Sakyi *et al*., 2022a; Wikiri, 2021
Data infrastructure and governance	Reliable pipelines, dashboards and privacy compliance enable trusted analytics	Analytics layer (pipeline and governance)	Agwuna *et al*., 2022; Atakpa and Abolaji, 2022; Badmus *et al*., 2019a; Ominyi and Anichukwueze, 2022a
Forecasting and business decisions	Prediction embedded in planning improves allocation and value creation	Outcomes; budget reallocation	Lawal and Oduleye, 2019b, 2021a; Tonoyan *et al*., 2021a; Unamma, 2022

1.7. Research Gap

Most published churn studies focus on contractual settings, such as telecoms, where churn is observed directly when a contract ends. Non-contractual retail settings, where customers simply stop buying, are less studied, and sports e-commerce in African markets is largely absent from the literature. Furthermore, few studies link churn predictions explicitly to the allocation of digital marketing budget across channels and customer tiers. This paper addresses these gaps.

1.8. Conceptual Model

1.8.1 Model Overview

Drawing on the synthesis, Figure 1 presents the conceptual model that guides the empirical study. The model has four layers. The first layer contains five families of customer data antecedents: transactional behaviour, digital engagement, service experience, relationship status and channel context. The second, the analytics layer, transforms these antecedents into predictions through a governed data pipeline and a machine learning retention model, and makes those predictions explainable through interpretation tools. The third, the decision layer, converts predictions into a churn-risk score and value at risk, assigns customers to risk tiers and diagnoses the drivers behind each customer's risk. The fourth layer translates these decisions into targeted marketing interventions and channel budget reallocation, which in turn drive retention and customer lifetime value. A feedback loop returns campaign outcomes to the data layer so that the model learns from each intervention, reflecting the human-in-the-loop and model monitoring principles identified in the literature (Ibe *et al*., 2022; Ladapo, Dosunmu, *et al*., 2022) [68, 76].

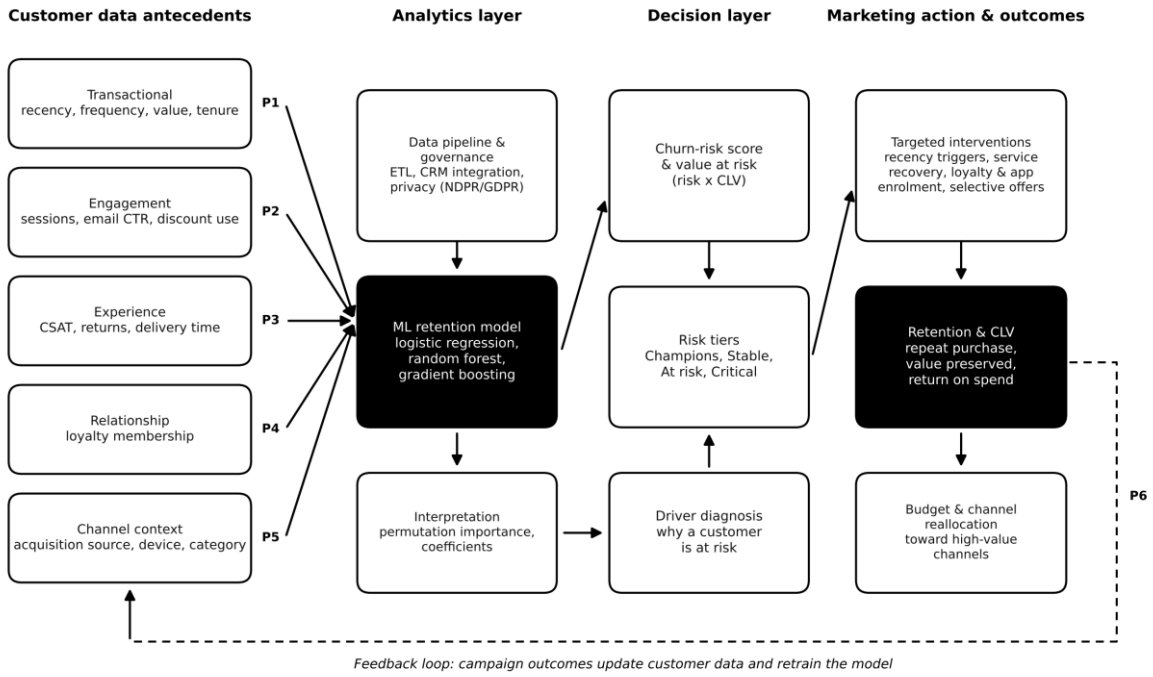


Fig 1: Conceptual model of machine learning-driven retention marketing in sports e-commerce

1.8.2 Propositions

The model implies six propositions, summarised in Table 2. Propositions P1 to P5 concern the antecedents of retention and are tested through the predictive model's coefficients and feature importance. Proposition P6 concerns the value of model-guided targeting and is tested through the campaign simulation.

Table 2: Propositions derived from the conceptual model

No.	Proposition	Grounding in literature
P1	Longer time since last purchase (recency) reduces the likelihood of retention, and recency is the strongest single predictor.	Fader, Hardie and Lee, 2005; Oziri *et al*., 2020
P2	Higher digital engagement (sessions, email click-through) increases retention, whereas dependence on discounts reduces it.	Ashore-Onisemo *et al*., 2021; Basnet *et al*., 2021; Wikiri *et al*., 2022
P3	Better service experience (higher satisfaction, fewer returns, faster delivery) increases retention.	Lemon and Verhoef, 2016; Feboh *et al*., 2022; Sakyi *et al*., 2022a; Wikiri, 2021
P4	Loyalty programme membership increases retention.	Kumar and Reinartz, 2016; Ezeako *et al*., 2019; Ukadike, 2022
P5	Acquisition channel and shopping device shape baseline retention, with owned, referral and app channels producing more loyal customers.	Sanni, Atima, *et al*., 2022; Seyi-Lande *et al*., 2020; Unamma, Okwesa, *et al*., 2018
P6	Under a fixed budget, model-guided targeting, especially when weighted by customer value, retains more customers and more value than untargeted outreach.	Verbeke *et al*., 2012; Ascarza, 2018; Atima *et al*., 2022; Sanni *et al*., 2020a

1.9. Structure of the Paper

The remainder of the paper is organised as follows. Section 2 presents the research method, covering both the literature synthesis procedure and the predictive modelling design. Section 3 presents the results and discussion, including the evaluation of the propositions and the theoretical and managerial implications. Section 4 concludes and sets out the limitations of the study and directions for future research.

2. Research Method

2.1. Research Design

The study adopted a two-strand design. The first strand is a structured, integrative literature synthesis that consolidates evidence on customer retention, predictive analytics, digital marketing, data infrastructure and governance, and operational execution, and uses it to build a conceptual model. The second strand is a quantitative predictive modelling study that operationalises the model, organised in five stages: (1) definition of the retention outcome; (2) feature engineering; (3) model training and validation; (4) model interpretation; and (5) translation into a marketing optimisation framework evaluated by campaign simulation.

2.2. Literature Identification and Synthesis Procedure

The literature synthesis drew on two pools of sources. The first comprised foundational works on customer retention, customer lifetime value, churn modelling, machine learning and interpretability that are widely cited in marketing science. The second was a consolidated bibliographic corpus of 1,296 records spanning marketing, information systems, finance, operations, governance and engineering research. Records were screened in three steps. First, titles and abstracts were assessed for direct relevance (customer retention, churn, marketing analytics, customer experience) or adjacent relevance (predictive risk modelling, data pipelines and business intelligence, data protection, process improvement and fulfilment). Second, works published after 2022 were excluded so that the evidence base reflects knowledge available during the study period. Third, retained works were coded into seven themes that map onto the components of the conceptual model. This process yielded 137 sources from the corpus, which together with 18 foundational works form a reference base of 155 sources. Evidence was synthesised narratively within each theme and then integrated across themes to derive the propositions presented in Section 1.8.

2.3. Data and Outcome Definition

The analysis used a cohort of 24,000 customer profiles whose structure mirrors FitandPro's customer records: acquisition source, primary product category, shopping device, order history, browsing activity, email engagement, discount usage, returns, satisfaction ratings, loyalty membership and delivery performance. To protect customer privacy and commercial confidentiality, in line with privacy-preserving analytics practice (Atakpa and Abolaji, 2022; Ominyi and Anichukwueze, 2022a) [35, 108], the modelling dataset was synthetically generated to reproduce the structure and the plausible relationships of the production data rather than drawn directly from individual customer records. All results reported below are computed on this dataset.

Because sports e-commerce is a non-contractual setting, retention was defined behaviourally: a customer was labelled retained (1) if they placed at least one further order within 180 days of the observation date, and churned (0) otherwise. Under this definition 63.6 percent of customers were retained, giving a churn rate of 36.4 percent.

2.4. Feature Engineering

Fourteen predictors were constructed, grouped into five families. They are summarised in Table 3. The selection draws on RFM theory and on prior studies that use engagement, service and channel variables to predict customer behaviour (Basnet *et al*., 2021; Oziri *et al*., 2020) [42, 118].

Table 3: Model features

Feature	Family	Description
Recency (days)	Transactional	Days since last order
Order count	Transactional	Total orders placed
Average order value	Transactional	Mean basket value (NGN)
Tenure (days)	Transactional	Days since first order
Monthly sessions	Engagement	Average site or app sessions per month
Email click-through rate	Engagement	Share of marketing emails clicked
Discount share	Engagement	Share of orders using a discount code
Return rate	Experience	Share of orders with a return
Customer satisfaction (CSAT)	Experience	Post-purchase rating, 1 to 5
Delivery days	Experience	Average days from order to delivery
Loyalty member	Relationship	Enrolled in loyalty programme (yes/no)
Acquisition channel	Channel	Paid search, social media, email, organic, influencer, referral
Primary category	Channel	Footwear, apparel, equipment, nutrition, accessories
Device	Channel	Mobile app, mobile web, desktop

2.5. Data Preparation

Numerical features were standardised to zero mean and unit variance. Categorical features were one-hot encoded. The data were split into a training set (75 percent, 18,000 customers) and a held-out test set (25 percent, 6,000 customers), stratified by the outcome so that both sets had the same retention rate. All preprocessing steps were fitted on the training data only and wrapped in a single pipeline to prevent information leaking from the test set, consistent with single-source-of-truth data quality practice (Unamma *et al*., 2019a) [146].

2.6. Models

Three classifiers were selected to represent different points on the trade-off between interpretability and flexibility:

- **Logistic regression** models the log-odds of retention as a linear combination of the features. It is fast, stable and directly interpretable, and served as the baseline.
- **Random forest** (Breiman, 2001) [45] averages 400 decision trees grown on bootstrap samples, capturing non-linearities and interactions. A minimum leaf size of five was used to limit overfitting.
- **Gradient boosting** (Friedman, 2001) [64] builds trees sequentially, each correcting the errors of the last. A histogram-based implementation was used with a learning rate of 0.05, up to 400 iterations, 31 leaves per tree and L2 regularisation.

All models were implemented in Python with scikit-learn (Pedregosa *et al*., 2011) [119].

2.7. Evaluation

Models were assessed with five-fold stratified cross-validation on the training set and then on the held-out test set. The primary metric was the area under the receiver operating characteristic curve (AUC), which measures how well a model ranks retained customers above churned ones and does not depend on a classification threshold. Accuracy, precision, recall and F1 score at a 0.5 threshold were also reported, together with the Brier score, which measures the accuracy of predicted probabilities. Feature influence was measured with permutation importance on the test set: the drop in AUC when each feature's values are randomly shuffled. This combination of discrimination, calibration and interpretability checks reflects current guidance on observable and interpretable models (Ibe *et al*., 2022; Komi and Adamolekun, 2021) [68, 74].

2.8. Marketing Optimisation Framework

Following Verbeke *et al*. (2012) [153], the business value of the model was assessed by simulating a retention campaign on the test set, an approach consistent with analytical models for measuring marketing return on investment and data-driven cost management (Oduleye and Medon, 2021; Sanni *et al*., 2020a) [97, 128]. The campaign assumptions were:

- A fixed budget allowing contact with 20 percent of customers (1,200 of 6,000).
- A cost of NGN 1,500 per contacted customer, covering incentive and delivery cost.
- A 25 percent probability that a contacted customer who would otherwise churn is retained by the campaign.
- Customer value estimated as average order value multiplied by annual order frequency (capped at 12 orders per year).

Three targeting rules were compared: random selection (the untargeted status quo), selection by highest predicted churn risk, and selection by predicted churn risk multiplied by customer value (expected value at risk).

3. Results and Discussion

3.1. Model Performance

Table 4 reports cross-validated and test-set performance. All three models achieved closely similar discrimination. Logistic regression recorded the highest test AUC (0.773) and the lowest Brier score (0.181), followed by random forest (0.768) and gradient boosting (0.765). Cross-validation results were stable, with standard deviations of about 0.005 across folds, and test-set results were consistent with cross-validation, indicating no material overfitting.

Table 4: Model performance (test set n = 6,000)

Model	CV AUC (SD)	Test AUC	Accuracy	Precision	Recall	F1	Brier
Logistic regression	0.770 (0.005)	0.773	0.726	0.743	0.872	0.802	0.181
Random forest	0.758 (0.005)	0.768	0.726	0.732	0.899	0.807	0.184
Gradient boosting	0.761 (0.005)	0.765	0.725	0.744	0.866	0.800	0.183

Given its marginally better accuracy, better-calibrated probabilities and full transparency, logistic regression was selected as the production model. This outcome is consistent with Christodoulou *et al*. (2019) [48]: when the main relationships in the data are close to monotonic and additive, a well-specified linear model can match more complex learners while being far easier to explain to marketing and management stakeholders. It also supports arguments for interpretable early-warning models and for keeping humans in the loop of automated decisions (Komi and Adamolekun, 2021; Ladapo, Dosunmu, *et al*., 2022) [74, 76].

3.2. Drivers of Retention

Figure 3 shows the ten most influential features by permutation importance. Recency dominated: shuffling it reduced AUC by 0.107, nearly three times the effect of any other feature. It was followed by customer satisfaction (0.039), loyalty membership (0.031), email click-through rate (0.028) and return rate (0.019). Monthly sessions, acquisition channel and delivery time made smaller but meaningful contributions. Average order value and order count contributed little once recency and engagement were known.

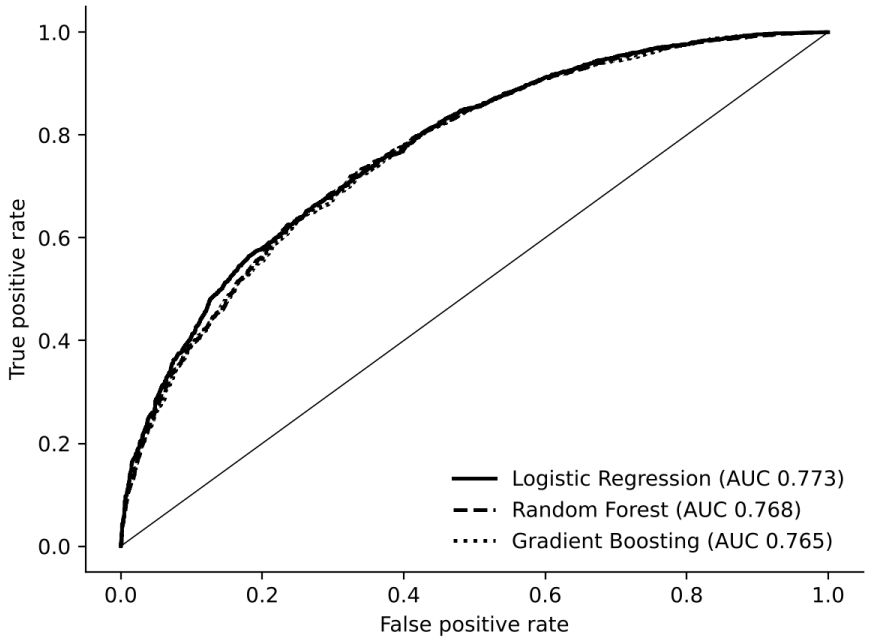


Fig 2: ROC curves for the three models on the held-out test set

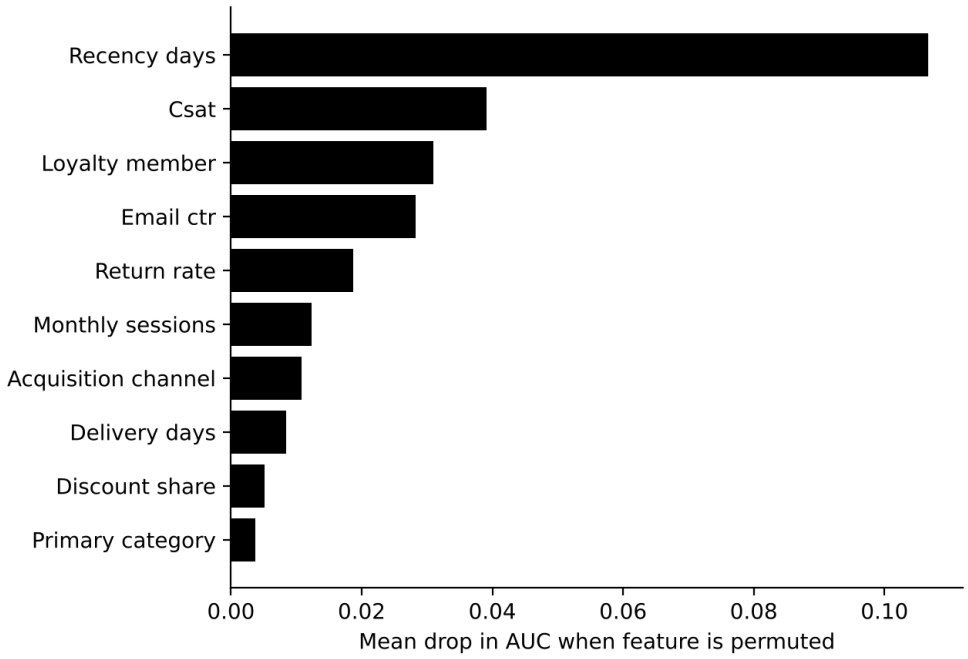


Fig 3: Permutation importance of the ten most influential features (logistic regression)

The direction of each effect, read from the standardised logistic regression coefficients, is intuitive. Longer time since the last order strongly reduced the odds of retention. Higher satisfaction ratings, loyalty membership, higher email click-through and more frequent sessions all increased them. Higher return rates, slower deliveries and heavy reliance on discount codes reduced them. The negative effect of discount dependence is notable for marketing practice, because it suggests that customers acquired and retained mainly through price promotions are less loyal. The importance of satisfaction and service is consistent with research linking customer service analytics and first-contact resolution to revenue and loyalty (Sakyi *et al*., 2022a; Wikiri, 2021) [125, 154].

3.3. Segment-Level Retention Patterns

Table 5 summarises observed retention across the main marketing segments. Customers acquired through email and referrals retained at about 70 percent, compared with 58.5 percent for social media and 60.4 percent for influencer campaigns. Mobile app users retained at 70.5 percent, well above mobile web (59.8 percent) and desktop (58.8 percent). Loyalty programme members retained at 74.5 percent against 58.4 percent for non-members. Among product categories, nutrition customers, whose purchases are naturally replenished, showed the highest retention (70.2 percent).

Table 5: Observed 180-day retention by segment

Segment	Group	Retention rate
Acquisition channel	Email	69.9%
	Referral	69.9%
	Organic	67.5%
	Paid search	62.9%
	Influencer	60.4%
	Social media	58.5%
Device	Mobile app	70.5%
	Mobile web	59.8%
	Desktop	58.8%
Loyalty programme	Member	74.5%
	Non-member	58.4%
Primary category	Nutrition	70.2%
	Footwear	64.6%
	Apparel	62.4%
	Accessories	61.5%
	Equipment	60.3%

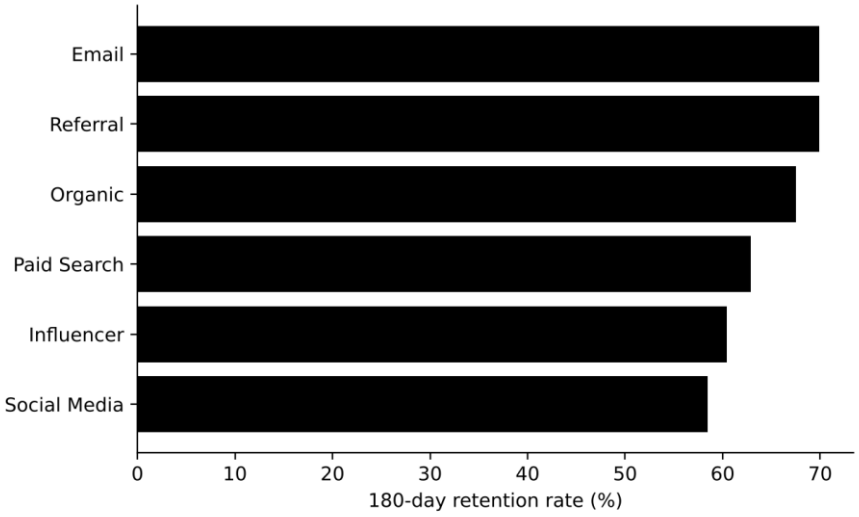


Fig 4: 180-day retention rate by acquisition channel

3.4. Risk Segmentation

Test-set customers were ranked by predicted churn risk and divided into ten equal deciles. Figure 5 shows that actual churn fell steadily from 82.3 percent in the highest-risk decile to 5.5 percent in the lowest. The top decile churned at 2.3 times the average rate, and the top two deciles together, just 20 percent of customers, contained 39.8 percent of all churners. This concentration is what makes targeted retention marketing efficient.

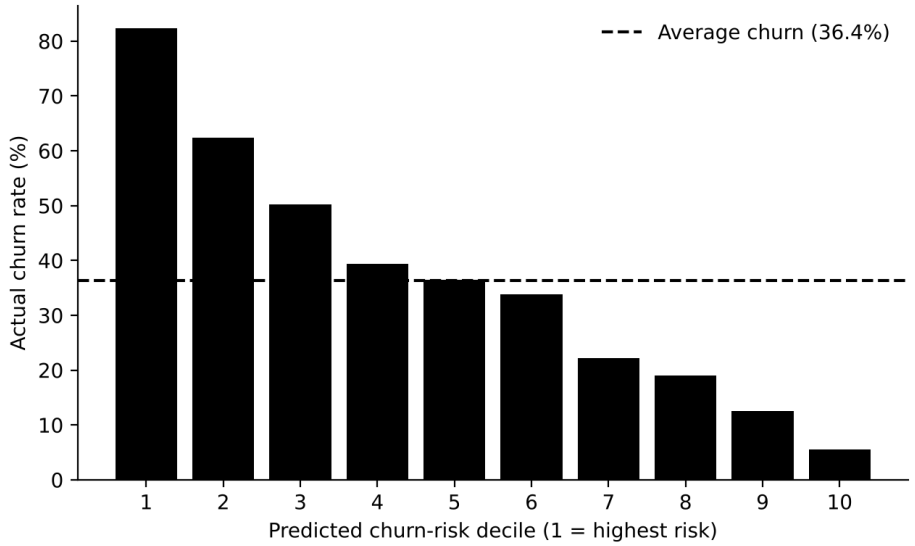


Fig 5: Actual churn rate by predicted risk decile

3.5. Campaign Simulation

Table 6 compares the three targeting rules under identical budgets of NGN 1.8 million. Ranking customers by predicted risk retained an estimated 217 customers, almost double the 112 retained by random targeting. Weighting risk by customer value retained fewer customers (170) but preserved the most value: an estimated NGN 57.3 million in annual customer value, 2.7 times the random baseline and 35 percent more than pure risk ranking.

Table 6: Simulated retention campaign outcomes (budget NGN 1.8 million, 1,200 contacts)

Targeting rule	Customers retained	Annual value preserved (NGN m)	Return on spend
Random (status quo)	112	21.1	10.7x
Highest churn risk	217	42.5	22.6x
Risk x customer value	170	57.3	30.8x

Return on spend is calculated as value preserved minus campaign cost, divided by campaign cost. Absolute figures depend on the assumed save rate and cost per contact and should be read as relative comparisons rather than forecasts. The ordering of the three rules, however, holds across any positive save rate, because model-guided rules always place more true churners, and more valuable churners, in the contacted group. These findings align with work showing that analytics-led allocation improves capital allocation and financial planning outcomes (Lawal and Oduleye, 2021a, 2021b) [80, 81].

3.6. Discussion

3.6.1 Answering the Research Questions

RQ1. Retention can be predicted with useful accuracy from routinely collected e-commerce data. An AUC of about 0.77 is in line with published churn models in non-contractual settings and, more importantly, is sufficient to concentrate churners strongly in the top risk deciles, as reported in comparable churn and lifecycle studies (Oziri *et al*., 2020) [118].

RQ2. Recency is by far the strongest single signal, confirming the enduring value of RFM thinking (Fader, Hardie and Lee, 2005) [60]. Beyond recency, the most important predictors are experiential and relational (satisfaction, returns, delivery speed and loyalty membership) and engagement-based (email click-through and sessions). Spending level matters much less than is often assumed.

RQ3. Model-guided targeting roughly doubled the number of customers retained and, when combined with customer value, nearly tripled the value preserved for the same budget. This is consistent with evidence that predictive segmentation reduces wasted marketing spend (Atima *et al*., 2022; Basnet *et al*., 2021) [36, 42].

3.6.2 Evaluation of the Propositions

The results support P1, P2, P3, P4 and P6, and partly support P5. Recency was by far the most important predictor and reduced retention as expected (P1). Sessions and email click-through increased retention, while discount dependence reduced it (P2). Satisfaction, return rate and delivery time all moved retention in the predicted direction (P3), and loyalty members retained at 74.5 percent against 58.4 percent for non-members (P4). Channel and device differences were visible in the segment analysis, with email, referral and app users retaining best, but their contribution to model performance was modest once behaviour and experience were known, so P5 is supported only partly: channel matters mainly because it shapes who the customer is and how they engage. The campaign simulation strongly supported P6.

3.6.3 Comparison with Prior Research

The findings align with the established view that recency carries most of the predictive information in purchase histories (Fader, Hardie and Lee, 2005) [60] and with churn studies in subscriber businesses (Oziri *et al*., 2020) [118]. The parity between logistic regression and ensemble models echoes the comparisons of Neslin *et al*. (2006) [94] and

Christodoulou *et al*. (2019) [48], and suggests that, for marketing teams, interpretability can be gained without sacrificing accuracy. The weight carried by experience variables supports customer journey research (Lemon and Verhoef, 2016) [83] and studies linking service analytics to revenue (Sakyi *et al*., 2022a) [125], and extends this evidence to sports e-commerce in an emerging market. The value of targeting reproduces, in a retail setting, the profit-based evaluation logic of Verbeke *et al*. (2012) [153], while the advantage of value-weighted targeting is consistent with Ascarza's (2018) [28] caution against chasing risk alone.

3.7. Theoretical Implications

The study makes three contributions to theory. First, it extends churn research from contractual settings to non-contractual sports e-commerce, showing that a behavioural definition of retention can be modelled reliably from routinely collected data. Second, the conceptual model integrates previously separate streams of work on customer lifetime value, predictive risk modelling, customer experience and data governance into a single chain running from antecedents to outcomes, and clarifies that prediction creates value only when connected to decision rules and interventions. Third, the findings refine the antecedent structure of retention: experiential and relational variables add substantial predictive power beyond RFM, while spending level adds little, suggesting that retention theory in digital retail should give greater weight to service experience and engagement quality (Sakyi *et al*., 2022a; Wikiri, 2021) [125, 154].

3.8. Managerial Implications

3.8.1 A Tiered Retention Playbook

The risk scores can be used to assign every active customer to a tier, each with its own objective, message and channel mix, as set out in Table 7.

Table 7: Risk-tiered retention playbook

Tier	Predicted churn risk	Objective	Recommended actions
Champions	Below 20%	Grow value	Early access to new releases, loyalty upgrades, referral rewards; no discounts
Stable	20% to 40%	Deepen engagement	Personalised content and product recommendations by category; app download prompts
At risk	40% to 65%	Re-engage	Triggered win-back emails and push notifications, service recovery for poor CSAT or late delivery, modest time-limited incentive
Critical	Above 65%	Rescue if valuable	Prioritise by value at risk; personal outreach or stronger offer for high-value customers; low-cost automated contact only for others

3.8.2 Optimising Digital Marketing Strategy

The results support six practical shifts in digital marketing strategy:

- **Act on recency triggers.** Because recency is the strongest predictor, automated journeys should start when a customer passes typical repurchase intervals for their category, for example 30 to 45 days for nutrition and longer for equipment, rather than on a fixed promotional calendar (Sanni, Iwuanyanwu, *et al*., 2022) [132].
- **Rebalance acquisition toward high-retention channels.** Acquisition budgets should be judged on the predicted lifetime value of customers acquired, not on cost per first order or last-click attribution (Sanni, Atima, *et al*., 2022) [131]. Referral and email-led acquisition deserve greater investment; social and influencer campaigns should be paired with onboarding journeys designed to lift their weaker retention, drawing on creator-economy evidence about building durable audiences (Anyanwu, 2021) [27].
- **Grow the app and loyalty base.** App users and loyalty members retain markedly better. Incentivising app installation and loyalty enrolment at or soon after the first purchase is likely to be one of the highest-return retention investments.
- **Fix experience before offering discounts.** Satisfaction, returns and delivery time all predict churn. A customer at risk because of a late delivery or a poor rating is better served by a service recovery message than by a generic discount (Sakyi *et al*., 2022a; Unamma *et al*., 2019b) [125, 147].
- **Reduce blanket discounting.** Heavy discount dependence was associated with lower retention. Incentives should be reserved for at-risk customers where the expected value saved exceeds the cost, applying the margin discipline advocated in cost-of-quality frameworks (Ashore-Onisemo *et al*., 2021) [31].
- **Target by value at risk, not risk alone.** Ranking by risk multiplied by value preserved the most revenue and partly addresses the concern raised by Ascarza (2018) [28] that the riskiest customers are not always the most worth saving. Data-driven cost management and financial planning analytics support the same value-focused allocation (Lawal and Oduleye, 2021b; Oduleye and Medon, 2021) [81, 97].

3.8.3 Implementation Implications

Implementing the model at FitandPro requires a modest data pipeline: a weekly scoring job that refreshes features from the order, web analytics, email and customer service systems, writes a risk score and tier to the customer relationship management (CRM) platform, and triggers the corresponding journeys in the email and push notification tools (Badmus *et al*., 2019a, 2022b) [38, 41]. A dashboard tracking retention rate by tier, campaign response and value preserved allows the marketing team to monitor impact (Sanni and Atima, 2021b; Seyi-Lande *et al*., 2022) [127, 134]. The model should be retrained quarterly, and its calibration checked monthly, because seasonality, such as football tournaments, New Year fitness resolutions and back-to-school periods, can shift purchasing patterns (Ibe *et al*., 2022; Tonoyan *et al*., 2021a) [68, 135].

The organisational side of implementation matters as much as the technical side. Lean and process-improvement research shows that analytics initiatives succeed when supported by documented standard operating procedures (Agboada *et al*., 2019; Eyetsemitan *et al*., 2022) [8, 58], standardised reporting and decision workflows (Alieme *et al*., 2022) [21] and

structured change management (Uzondu *et al*., 2021) [152], with success measured through multi-dimensional evaluation of the change programme (Obukadata *et al*., 2022) [96]. Lean Six Sigma adaptations for small enterprises (Ambali *et al*., 2021) [22], process re-engineering to cut cycle time (Ebisi, Okoli, *et al*., 2021; Oyeleye *et al*., 2022) [50, 117] and quality management systems that integrate Six Sigma and Lean (Okoli, Uzondu, *et al*., 2022) [100] offer practical templates for embedding the retention process in daily operations. Broader work on digital transformation in operations (Agboada *et al*., 2018) [7], compliance workflow design (Eyetsemitan *et al*., 2021) [57], multi-stakeholder governance alignment (Eyetsemitan *et al*., 2020) [56] and supply chain governance across retail networks (Akin-Oluyomi and Akhigbe, 2022) [15] completes the picture. Because retention depends on fulfilment, procurement process automation and supplier relationship management also matter (Akinleye and Adeyoyin, 2021, 2022b; Ike *et al*., 2021) [17, 18, 70], as do integrated product innovation cycles that keep the offer fresh for returning customers (Oluwo *et al*., 2022) [106]. Finally, strategic accounting systems and compliant financial reporting provide the measurement discipline for tracking the programme's return (Bola-Sadipe *et al*., 2019; Medon and Oduleye, 2022) [43, 92].

4. Conclusion

4.1. Summary of Findings

This paper has shown that a machine learning model built from standard e-commerce data can identify sports e-commerce customers at risk of churning with useful accuracy, and that using these predictions to direct retention spending substantially improves marketing efficiency. A transparent logistic regression model performed as well as more complex ensemble methods, making it well suited to a marketing environment where explanations matter. The analysis points to recency, customer experience, loyalty and engagement, rather than spending level, as the levers that most influence whether customers return. For FitandPro and similar sports e-commerce businesses, the central recommendation is to treat retention as a managed, model-guided process: score every customer, act early on recency signals, invest in the channels and programmes that produce loyal customers, and allocate incentives according to the value at stake.

4.2. Limitations

Several limitations should be noted. First, the modelling dataset was synthetically generated to reflect the structure of FitandPro's customer records rather than drawn directly from them, so absolute performance figures may differ when the model is applied to live data. The workflow itself transfers directly, but the model must be re-estimated and validated on production data before deployment. Second, the campaign simulation relies on assumed save rates and costs, so the absolute value estimates should be treated as illustrative. Third, the model predicts who is likely to leave, not who will respond to an intervention, and therefore cannot by itself identify the customers whose behaviour a campaign would change. Fourth, the 180-day retention window and the 0.5 classification threshold are design choices that may not suit every product category. Finally, the literature synthesis was limited to works published up to 2022 and to a single consolidated corpus, so relevant studies outside that corpus may have been missed.

4.3. Future Research

Several directions follow. First, the model should be validated on FitandPro's production data and tested prospectively, with randomised controlled campaigns and holdout groups used to measure the true effect of retention offers. Second, future work should develop uplift models that estimate the incremental effect of each campaign on each customer, building on the argument of Ascarza (2018) [28]. Third, additional data sources, such as product review text, social media interactions and on-site search queries, could improve prediction and help explain why customers leave (Iziduh *et al*., 2020) [73]. Fourth, survival and time-to-event models could predict when a customer is likely to lapse, not just whether, allowing journeys to be timed more precisely. Fifth, the fairness of targeting rules should be audited so that retention offers are not allocated in ways that disadvantage particular customer groups, with human oversight retained over automated decisions (Ladapo, Dosunmu, *et al*., 2022) [76]. Finally, comparative studies across sports retailers and across African markets would test how far the conceptual model generalises.

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