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Online newspaper subscriptions: using machine learning to reduce and understand customer churn

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ABSTRACT
Modelling customer loyalty has been a central issue in customer relationship management, particularly in digital subscription business models. To guarantee news media sustainability, publishers implemented subscription models that need to define successful retention strategies. Thus, churn management has become pivotal in the media subscription business. The present study aims to understand what drives subscribers to churn by performing a Machine Learning approach to model the propensity to churn of online subscribers of a Portuguese newspaper. Two models were developed, tested, and evaluated in two timeframes. The first one considered all Business to Consumer (B2C) subscriptions, and the second only the B2C non-recurring subscriptions. The experimental results revealed important patterns of churners, which allowed the marketing and editorial teams to implement churn prevention and retention measures.

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KEYWORDS
Churn prediction; online subscriptions; data mining; digital journalism; reader engagement

Introduction

News media traditionally base their business models on a combination of sales and advertising revenue (Fletcher & Nielsen, 2017). The economic recovery from the 2008 crisis (Arrese, 2016) and the recent COVID-19 pandemic, coupled with a digital transformation and reader habits changes, induced publishers to re-evaluate their business models (Newman, Fletcher, Robertson, et al., 2022). To diminish and offset the obstacles caused by the previously mentioned difficulties, newspaper companies are focusing on digital information business models (Cardoso et al., 2020).

Online newspapers' primary sources of revenue are advertising and online subscriptions, mainly in the form of paywall models (Pattabhiramaiah et al., 2019). Nonetheless, the first does not create a long-lasting relationship with the users and can be avoided with the use of ad blockers (advertisement blockers). Hence, the latter has been adopted by many publishers to increase revenue through subscription business models (Newman et al., 2019).

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Recent studies present new paywall mechanisms based on data science algorithms to define the optimal paywall time to increase the propensity to subscribe (Chakraborty et al., 2017; Davoudi, 2018) and to recommend engaging content to increase reader loyalty and subscription propensity (Abdollahpouri et al., 2021). Thus, publishers focus on subscriber acquisition and retention (Rußell et al., 2020).

Furthermore, reader retention, personalisation, and paywall models are some of the major points of concern in the industry (Rußell et al., 2020; Suárez, 2019). Moreover, improving churn is becoming more important than acquisition. A slight improvement in decreasing churn significantly impacts company results (Suárez, 2019). As the research on engagement drivers to retain or churn online reader subscribers is quite scarce (Fernandes et al., 2023), this research presents a valuable contribution to the media industry with a strategy to retain online subscribers by increasing reader loyalty and decreasing churn propensity.

As Kotler et al. (2019) argued, publishers should map the reader path across the reader funnel to improve critical touchpoints, such as cancelation moments. Furthermore, each second of time results in dozens of readers interacting with the website, which provides large volumes of data. Moreover, the opportunity to acquire more knowledge from the readers to implement successful acquisition and retention measures showed publishers that their extant database is their most valuable asset (Coussement & Van den Poel, 2009). The Big Data landscape makes the process of Data Mining (DM) part of an overall strategy to improve business intelligence, Customer Relationship Management (CRM), and Churn Management (Gunnarsson et al., 2007).

Between 2019 and 2020, there was a generalised increase in people paying for online news (Newman et al., 2021). However, in Portugal, 10% of the population affirmed paying for online news, most of them with an ongoing subscription (Cardoso et al., 2020). Portugal is still characterised by a strongly traditional press industry, where revenue depends highly on print (Newman, Fletcher, Schulz, et al., 2022). Even though digital media subscribers are increasing, the figures are small, threatening this trusted Portuguese news ecosystem. In addition, a wide variety of accessible options for readers poses a challenge to the newspaper business on digital platforms (Cardoso et al., 2020).

In this exploratory research, we used data from PÚBLICO online users. PÚBLICO is one of the Portuguese newspapers with the highest national reach, a trusted brand with well-defined journalistic values, and a digital subscription leader (Newman et al., 2020). This study has two main goals. First, identifying readers with the likelihood of churn, and second, understanding the main drivers of loyalty, retention, and churn is pivotal for publishers (Fernandes et al., 2024; Rußell et al., 2020). The objective is that the subscription marketing team can act in time to retain those subscribers with a high propensity to churn. With this understanding into consideration, this study aims to answer the following research questions (RQs):

(1) Can a Machine Learning (ML) model identify subscribers most likely to churn?
(2) What factors impact subscription renewal?
(3) What are the patterns of churn subscribers?
(4) Can retention strategies reduce the churn rate?

By answering these RQs, this study aims to contribute to the literature on publishers' churn management and to guide publishers ' subscription marketing teams on how to act in time to retain subscribers.

Theoretical background

Customer churn

In today's digital subscription business models (DSBMs), to guarantee sustainability, companies highly value having a customer-oriented business strategy (Uner et al., 2020). One of the main challenges in this strategy is churn management, a very well-studied topic in literature. Research considerers that there are two types of churn: incidental and deliberate (Jayaswal et al., 2016). Incidental churn occurs when customers are forced to end their subscriptions for underlying reasons (e.g. faulty payments). In contrast, the process of a customer voluntarily deciding to cancel their subscription falls under the deliberate churn definition. The present research focuses on deliberate churn, a vital topic in online newspapers with subscription models (Rußell et al., 2020).

It is argued that reader retention is related to the frequency with which a user reads (Davoudi, 2018). Reader engagement is considered a multidimensional phenomenon related to the level of attention and involvement (emotional, cognitive, and behavioural) with media (Attfield et al., 2011; Fernandes et al., 2024). Several researchers have studied the relationship between user engagement and purchase intention in DSBMs. However, research on the relationship between engagement and cancelation is scarce in the media industry. Using a predictive model to detect customers' likelihood of terminating their relationship with a company has proven to be very important. Thus, media companies invest in churn management for numerous reasons, namely:

(1) Take advantage of the information they already have about long-term customers. With that information, they can understand their needs, preferences, and consumption characteristics. By increasing cross-sell and up-sell actions, customers become more profitable. Furthermore, a satisfied customer provides positive referrals that consequently bring new customers (Ganesh et al., 2000).
(2) A small change in the churn rate can significantly increase profitability (Coussement & Van den Poel, 2009).
(3) Conversely, unsatisfied customers can spread the word in diverse channels, inducing other customers to churn (Nitzan & Libai, 2011) and decreasing brand value.
(4) Moreover, profit is compromised to attract new customers as the pressure for acquisition induces a price reduction and acquisition costs increase (De Caigny et al., 2018). Acquiring a new customer is several times more expensive than retaining existing ones (Kotler et al., 2016).

Churn prediction in subscription business models

Studies on customer churn prediction in the media sector have been developed by some authors (Burez & Van den Poel, 2007; Yuan et al., 2017). The digital database Scopus, the largest abstract and citation database of peer-reviewed literature (Ballew, 2009), only returns 39 documents (as of December 2023) that included the terms “churn” and “publisher”/”newspaper”:

TITLE-ABS-KEY (churn AND (publisher OR newspaper)) AND PUBYEAR > 1999 AND PUBYEAR < 2024

In these 39 documents, some interesting churn analyses across industries can be found (Ahn et al., 2020; C.-F. Tsai & Lu, 2010). There are examples from the online game industry (Xiong et al., 2023) and media industry (Coussement & Van den Poel, 2008), as well as a study that analyses online readers churn by device (Peña et al., 2023). Other studies on the matter have been developed in telecommunication (Coussement et al., 2017; Keramati et al., 2014; Verbeke et al., 2012), banking (Farquad et al., 2014), gambling (Coussement & De Bock, 2013), and many other industries (e.g. De Caigny et al., 2018). However, literature on the application of ML in the media industry for churn modelling is quite scarce. Table 1 summarises the most prominent studies on churn modelling in subscription models. Traditional approaches such as Logistic Regression and Support Vector Machines have been employed to identify key predictors in subscription churn (De Caigny et al., 2018). However, the complexity and non-linearity of subscription data need more sophisticated models. Recent studies advocate for the adoption of advanced ensemble learning techniques like XGBoost (Chen & Guestrin, 2016) or LightGBM (Ke et al., 2017) due to their superior performance in handling large-scale, high-dimensional datasets with improved accuracy and efficiency.

Across the media industry, some churn management strategies and insights have been published (Suárez, 2019). Dagens Nyheter, a Swedish newspaper, has created a research engine that pinpoints over 200 features that explain churn (Southern, 2019). They identify the lack of frequent visits as the most common churn driver. In addition, direct debit payment methods and subscribers’ seniority are drivers of low churn, while monthly invoice reminders are drivers of high churn (SparkBeyond Team, 2021). On the other hand, The Economist favours the time on the website as the single biggest predictor of retention (Suárez, 2019). Other good indicators for churn are the number of premium articles read, consumption across devices, the channel used when a user converted, and whether a user hit the paywall or subscribed to a premium article (Campbell, 2018). In addition, the platform used to consume news has been shown to impact the subscribers’ willingness to renew their subscriptions, especially on mobile websites, underscoring the need to improve users’ experience across platforms (Peña et al., 2023).

Although metrics that support publishers in identifying probable churners may vary, subscribers’ engagement metrics (Davoudi et al., 2019) are the most used. Furthermore, most newspapers agree that building product usage habits helps sustain a longer relationship with customers and, consequently, reduces churn propensity (Davoudi, 2018).

Methodology

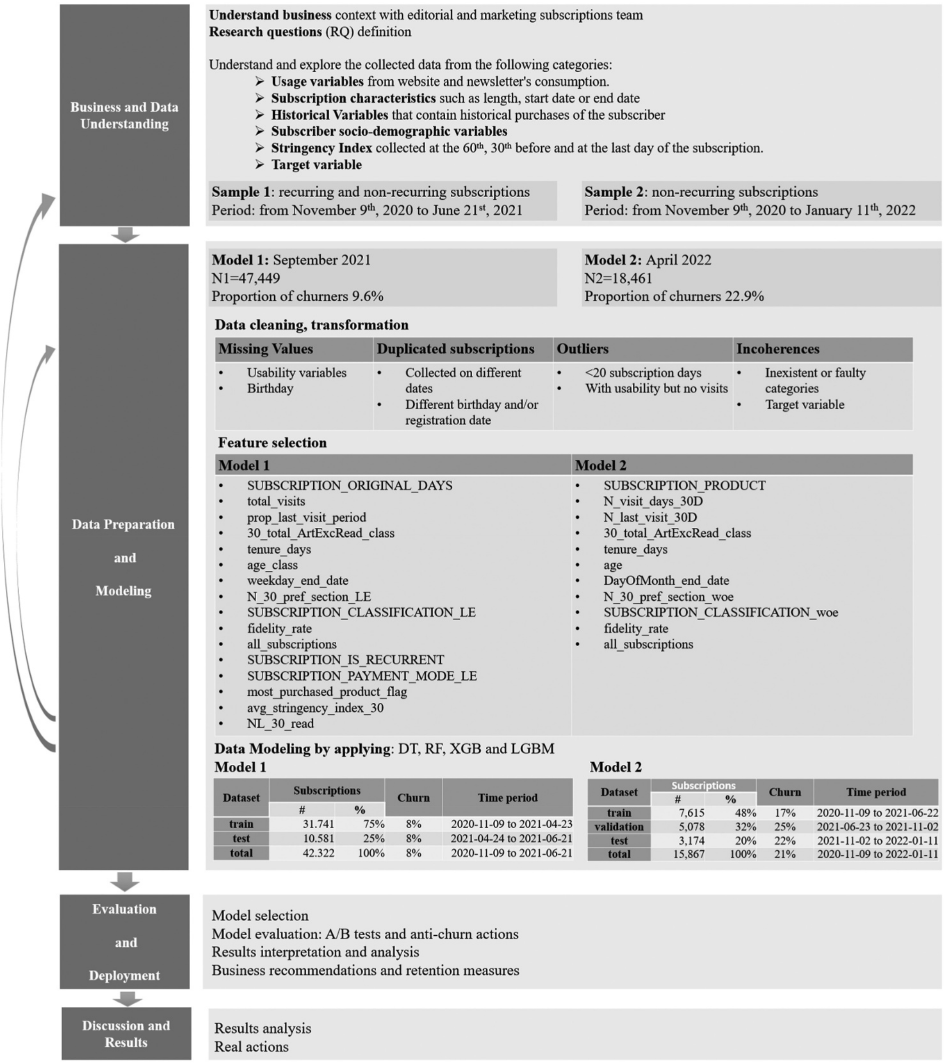
This study followed the well-known process model Cross Industry Standard Process for Data Mining (CRISP-DM) (Chapman et al., 2000). We combined business validation similarly to the Business Success Criteria of the CRISP-ML(Q) (Hanzelik et al., 2022). Thus, this section follows six phases, describing the going back and forward between the

Table 1. Literature review on churn modelling in subscriptions business models.

Authors	Model	Results (R) and limitations (L)
De Caigny et al. (2018)	Support Vector Machines (SVM)	R: the SVM model outperforms a Random Forest (RF) algorithm; the ten most important predictors were extracted. The subscription's length and the elapsed time since the last renewal are the most important predictors L: print newspaper subscription context; client-company interaction data was not considered; monetary value, frequency of renewals, and sociodemographic variables were not present in the most important variables
MittMedia (Ekholm, 2019)	Survival Analysis, Gradient Boost Machine (GBM), and Neural Network (NN)	R: Swedish media business uses models that complement each other in the churn prediction analysis. Insights into variables correlated with churn show that a high count of notification openings and female users were more correlated to churn. In contrast, a higher count of articles read or if the subscriber was a past paper subscriber were more correlated with a lower churn risk. Retention actions are focused on users with a likelihood to churn between 60% and 90%. L: scarce information about the data preparation and model performance.
Burez and Van den Poel (2007)	Logistic Regression (LR), Markov Chains, RF	R: Historical and current subscription data, socio-demographic data, and interactions with the customer churn prediction were studied on an imbalanced dataset (15% churners). The study results show that for cut-off values lower than 25%, the RF model outperforms other techniques; however, for larger cut-off values, both LR models perform as well as the RF and end up surpassing it. L: pay-TV sector.
(2006)	LR, Decision Tree (DT) with Bagging, Stochastic Gradient Boosting	R: Bagging and boosting classification techniques to predict churn have similar performance, nevertheless, bagging is considered the most competitive approach since it is conceptually less complicated than stochastic gradient boosting. Random oversampling applied to half of the training set keeping the other half of the training set with the original distribution (1.8% churn), show that a balancing schema was preferable. Adjusting the cut-off value is substantially better than assigning a weight to each observation in the training set. L: telecommunication sector; very small churn rate.
C. Tsai and Lu (2009)	NN, Self-Organizing Maps	R: By sequentially combining NN with NN and Self-Organising Maps with NN, the first technique filtered out unrepresentative training data, then, the second used the representative outputs to create the prediction model. Results indicated that the single NN was outperformed by both hybrid models in accuracy and Type I and II errors, being the combination of two NN the best performing model. L: telecommunication sector; black-box models.

phases in multiple iterations until the result is reached. A diagram of the sequence of the phases is detailed in Figure 1.

Like in many online subscription models, PÚBLICO has two types of subscriptions: recurring (automatically renewed) and non-recurring (non-automatically renewed). Non-recurring subscriptions are made with one-off payment transactions (e.g. bank transfers) and are associated with higher churn rates. Since churn rates differ in the two types, two models were built to conduct two experiments. Model 1 predicts churn for recurring and non-recurring subscriptions, and Model 2 predicts churn only for non-recurring subscriptions (see Figure 1). The models were



Business and Data Understanding

Understand business context with editorial and marketing subscriptions team
Research questions (RQ) definition

Understand and explore the collected data from the following categories:

- **Usage variables** from website and newsletter's consumption.
- **Subscription characteristics** such as length, start date or end date
- **Historical Variables** that contain historical purchases of the subscriber
- **Subscriber socio-demographic variables**
- **Stringency Index** collected at the 60th, 30th before and at the last day of the subscription.
- **Target variable**

Sample 1: recurring and non-recurring subscriptions
Period: from November 9th, 2020 to June 21st, 2021

Sample 2: non-recurring subscriptions
Period: from November 9th, 2020 to January 11th, 2022

Data Preparation and Modeling

Model 1: September 2021
N1=47,449
Proportion of churners 9.6%

Model 2: April 2022
N2=18,461
Proportion of churners 22.9%

Data cleaning, transformation

Missing Values	Duplicated subscriptions	Outliers	Incoherences
• Usability variables • Birthday	• Collected on different dates • Different birthday and/or registration date	• <20 subscription days • With usability but no visits	• Inexistent or faulty categories • Target variable

Feature selection

Model 1	Model 2
• SUBSCRIPTION_ORIGINAL_DAYS • total_visits • prop_last_visit_period • 30_total_ArtExcRead_class • tenure_days • age_class • weekday_end_date • N_30_pref_section_LE • SUBSCRIPTION_CLASSIFICATION_LE • fidelity_rate • all_subscriptions • SUBSCRIPTION_IS_RECURRENT • SUBSCRIPTION_PAYMENT_MODE_LE • most_purchased_product_flag • avg_stringency_index_30 • NL_30_read	• SUBSCRIPTION_PRODUCT • N_visit_days_30D • N_last_visit_30D • 30_total_ArtExcRead_class • tenure_days • age • DayOfMonth_end_date • N_30_pref_section_woe • SUBSCRIPTION_CLASSIFICATION_woe • fidelity_rate • all_subscriptions

Data Modeling by applying: DT, RF, XGB and LGBM

Model 1

Dataset	Subscriptions		Churn	Time period
	#	%		
train	31.741	75%	8%	2020-11-09 to 2021-04-23
test	10.581	25%	8%	2021-04-24 to 2021-06-21
total	42.322	100%	8%	2020-11-09 to 2021-06-21

Model 2

Dataset	Subscriptions		Churn	Time period
	#	%		
train	7,615	48%	17%	2020-11-09 to 2021-06-22
validation	5,078	32%	25%	2021-06-23 to 2021-11-02
test	3,174	20%	22%	2021-11-02 to 2022-01-11
total	15,867	100%	21%	2020-11-09 to 2022-01-11

Evaluation and Deployment

Model selection
Model evaluation: A/B tests and anti-churn actions
Results interpretation and analysis
Business recommendations and retention measures

Discussion and Results

Results analysis
Real actions

Figure 1. Research framework.

sequentially evaluated, with daily predictions being subject to A/B tests. One group was contacted with retention actions (variation group), and no action was applied to the control group. Both experiments underwent a similar preprocessing phase: data was cleaned, transformed, and filtered. The modelling and respective evaluation phases followed the same framework for each model (see diagram in Figure 1). The analysis was done using the Python programming language and relying mainly on the following Python packages: pandas (McKinney, 2010), Scikit-learn (Pedregosa et al., 2011), XGBoost (Chen & Guestrin, 2016), and LightGBM (Ke et al., 2017). XGBoost and LightGBM are scalable gradient-boosting machine learning algorithms that achieve state-of-the-art results by optimally combining decision trees, utilising advanced regularisation techniques, and employing efficient computation strategies.

Business and data understanding

PÚBLICO's online subscription retention problem was tackled through churn prediction, formalising it as a supervised ML research for binary classification. The target variable was defined as a churner (1) if a customer did not renew the subscription 30 days after the renewal date; otherwise, the customer was classified as a non-churner (0). Two sets of B2C subscribers were studied (Sample 1 and Sample 2; see description in Figure 1). Each dataset contains 44 features: customers' website usage and newsletters consumption, subscription product specifications, user-related variables, and historical information focused on users' affiliation with the company. Sample 1 contained 47,449 subscriptions, and sample 2 had 18,461 subscriptions, respectively, with a churn rate of 9.6% and 22.9%. Non-recurring payments are one-off transactions and lead to a higher churn rate. Thus, performing a second model gave more focus to those subscribers.

The datasets covered, respectively, a period of subscription renewal dates from NaN Invalid Date NaN, to NaN Invalid Date NaN, and from NaN Invalid Date NaN, to NaN Invalid Date NaN. Data were collected 30 days after the subscription ended, along with a subscription status identifier (target value). Five groups of variables were collected (see Table 2).

Data preparation

Data preparation and preprocessing are critical phases in the DM process, as they are when representational data and its quality are addressed (Antonio et al., 2018). Finding patterns while training the algorithms is more complex and challenging when irrelevant, redundant, unreliable, or noisy data are present (Pyle, 1999). In this study, data cleaning comprises four tasks (see Figure 1):

- Process missing values and outliers. The website's usability variables with missing values were considered as having no interaction. Only subscribers with ages between 18 and 100 were considered, and missing values in the users' age were replaced with the average subscribers' age.
- Duplicate data can bias the model to predict those entries better. Hence, its removal was done by keeping the most accurate unique entries.
- Outlier elimination ensures that only representative data is introduced to the model. Therefore, subscriptions with less than 20 days were excluded as these involved offering subscribers a temporary subscription before the actual subscription began. Also, subscriptions without visits but with any kind of engagement were removed.
- A coherence check is indispensable to ensure the data can be reliable. Inexistent categories in the preferred content section variable meant the user did not log in during the month. Mismatching subscription durations were adjusted by computing the difference between the subscriptions' start and end dates. Furthermore, some inconsistencies were found and rectified within the subscription's classification. Keeping unique instances and removing the outliers reduced the size of the datasets by 10.8% in the first sample and 10.1% in the second.

Table 2. Features meaning, and periods covered.

	Variable Name	Type	Variable meaning	Period
Usage Variables	M_RFV_60D M_RFV_30D	Ordinal (e.g.: 597, 981, . . .)	Maximum RFV (Recency, Frequency, Volume) value	0D – 30D & 30D – 60D
	N_visit_days_60D N_visit_days_30D	Numerical	Number of days with visits	
	N_last_visit_60D N_last_visit_30D	Numerical	Days since the last visit	
	N_articles_N30 N_articles_N60	Numerical	Total articles read	
	N_exclusive_60D N_exclusive_30D	Numerical	Total exclusive-to-subscriber articles read	
	N_readability_75_60D N_readability_75_30D	Numerical	Total articles in which 75% of the article was read	
	engagement_Share_60D engagement_Share_30D	Numerical	Number of shares from the website to social media	
	engagement_COMENT_60D engagement_COMENT_30D	Numerical	Number of comments on the website	
	engagement_save_60D, engagement_save_30D	Numerical	Number of articles saved on the website	
	N_30_pref_section	Categorical (e.g.: Society, Politics)	Preferred content section	0D – 30D
	NL_30_read	Numerical	Number of newsletters read	
	NL_30_click		Number of newsletters clicked	
Subscription Characteristics	A1_SUBSCRIPTION_ CAMPAIGN	Categorical (e.g.: Pense bem Pense Publico, Paywall, . . .)	Campaign related with current subscription	Subscription length
	end_date	Date	Subscription's end date	
	start_date	Date	Subscription's start date	
	SUBSCRITPION_CHANNEL	Categorical (e.g.: Online store, Call centre contact)	Channel through which the subscriber purchased the current subscription	
	SUBSCRIPTION_TYPE	Binary	Binary indicating if the subscription is paid or offered	
	SUBSCRIPTION_PRODUCT	Ordinal (e.g.: month, semester)	Subscription product duration	
	SUBSCRIPTION_PAYMENT _MODE	Categorical (e.g.: credit card, paypal, . . .)	Payment method used	
	SUBSCRIPTION_ ORIGINAL_DAYS	Numerical	Subscription length in days	
	SUBSCRIPTION_IS _RECURRENT	Binary	Binary indicating if the subscription is automatically renewed	
	SUBSCRIPTION_IS_TRIAL	Binary	Binary indicating if the price increases in the next subscription	
	SUBSCRIPTION_VALUE _WITH_TAXES	Numerical	Subscription price	
	SUBSCRIPTION _CLASSIFICATION	Categorical (e.g.: renovation, new client, . . .)	Customer's relationship with the company at the purchase moment	
Historical Variables	all_subscriptions	Numerical	Total subscriptions	Since the user registered the website
	avg_subscription_days	Numerical	Average subscription length in days	

(*Continued*)

Table 2. (Continued).

	Variable Name	Type	Variable meaning	Period
	max_subscription_days	Numerical	Maximum subscription length in days	
	tenure_days	Numerical	Days since the first subscription	
	fidelity_rate	Numerical	e_active_subs_days/ c_tenure_days	
	active_subs_days	Numerical	Days with active subscriptions	
	i_product1	Numerical	Most purchased subscription length in days	
	USER_create_date	Date	Subscriber registration on the website	
Subscriber Socio demographics	gender	Categorical (e.g.: male, female)	Subscriber gender	
	birthday	Date	Subscriber birthday	
	job	Categorical (e.g.: lawyer, teacher, artist, . . .)	Subscriber job	
Target	SUBSCRIPTION_IS_ACTIVE	Binary	Binary indicating if the subscription is active	30D after subscription ends
Stringency Index	avg_stringency_index_30, avg_stringency_index_60, avg_stringency_index_total	Numerical	Average stringency index (Global Change Data Lab, 2021)	0D – 30D, 30D – 60D, 0D – 60D

Having many available features that interact with each other, new variables were defined. For usability variables, in which there was available data for the last two months before the subscription ended, the following measures were derived:

- The sum of activity in both periods, i.e. total articles read in both periods.

$$N\_articles\_N30 + N\_articles\_N60$$

- The proportion of activity per period, i.e. the percentage of articles read in the first or second period, highlights which period the user was more engaged.

$$\frac{N\_articles\_N30 - N\_articles\_N60}{N\_articles\_N30 + N\_articles\_N60}$$

- Average activity per day for each period and both periods aggregated.

$$\frac{N\_articles\_N30}{N\_visit\_days\_30D}$$

- Binning usage metrics for each period according to percentiles (e.g. N_articles_N30 divided in 20th percentiles) and the days with visits by the days in a month, this way reducing the impact of extreme values on the model's performance.

Furthermore, binary variables were created to indicate user interaction with the website features (such as comment, share, or save). The maximum RFV values were split into three columns, each indicating a value of the RFV variable. For newsletters, the click-through rate, the sum of the clicks and openings, and a binary variable for user newsletter interaction were computed.

We derived the subscriber's age at the end of the subscription from the birthday. The start and end dates of the subscription were transformed into the weekday and the day of the month. The registration date was transformed into days since the user registered. Variables of days since the first subscription (tenure_days) and days with active subscriptions (active_subs_days) were converted into years.

A binary variable was computed to determine if the current product was the subscribers' most frequent choice and the average price per day on the current subscription.

Finally, the SUBSCRIPTION_PRODUCT was unified into three classes comprising monthly, quarterly and semi-annual, and annual or larger subscriptions. Classes with less than 5% of instances were aggregated into one, defined as the "other". As most ML algorithms cannot use text to perform predictions, these variables were transformed using label encoding and weight of evidence techniques.

Data modeling

Feature selection plays a key role in the model's performance and computational costs. Selecting a small but highly predictive subset of variables reduces collinearity issues and increases model interpretability (Verbeke et al., 2012). Thus, the features gender and job were removed (which had, respectively, 33% and 95% of missing values), along with features that indicated unreliable data during the coherence check process (e.g. avg_subscription_days, max_subscription_days).

Groups of features representing the same type of information were identified to perform feature selection. An initial predictor group with one variable per group was created, defining a base dataset constituted by features representing distinct information. To select one variable from each information group, the initial predictor group was used to compute XGBoost models (Chen & Guestrin, 2016), in which all variables were constantly present in the models, except for the predictor that was being analysed, which was sequentially replaced by all other variables on that information group. The evaluation F1 Score (F1), gain, cover, and weight importance were extracted. For each information group, ranks and an average of the ranks were assigned to the variables based on each metric. The variable in each information group with the lowest average rank was selected. To understand each feature's importance, the SHAP value was calculated. SHAP (SHapley Additive exPlanations) provides explanations for individual predictions by quantifying the contribution of each feature to the prediction. SHAP values are based on cooperative game theory. Shapley values assign a value to each player in a cooperative game based on their marginal contribution to every possible coalition. In the context of machine learning, each feature is considered a "player", and the prediction outcome is considered the "payoff" (Lundberg & Lee, 2017).

Following variable selection, the variables with absolute Pearson correlation (Taylor, 1990) over 0.75 were replaced with an equivalent variable in a different format, keeping the variable with the largest churn correlation. A sequential variable removal was conducted, and variables were removed if the model's F1 increased. The final training sets contained 16 and 11 predictors for Models 1 and 2, respectively (see Figure 1).

Table 3. Parameters considered for grid search cross-validation per model.

	XGBoost	LightGBM	Random Forest	Decision Tree
learning rate	[0.1, 0.2, 0.5]	[0.01, 0.1, 0.2]		
max_depth	[2, 3, 5, 7]	[−1, 2, 3, 5, 7]	[None, 2, 3, 5, 7]	[None, 2, 3, 5, 7,8]
n_estimators	[200, 500, 1000]	[200, 500, 1000]	[200, 500, 1000]	
base_score	[0.2, 0.5]			
colsample_bytree	[0.5, 0.8]	[0.5, 0.8]	["auto", 5, 8]	[None, 5, 8]
subsample	[0.3, 0.5, 0.8]	[0.3, 0.5, 0.8]		
gamma	[1, 20, 50, 100]			
min_samples_leaf		[None, 100, 200]	[1, 100, 200]	[1, 100, 200]
num_leaves		[5, 10, 20, 30]		
subsample_for_bin		[500, 1000, 200000]		

During the modelling stage, preprocessed datasets were sorted by subscriptions' end date. For Model 1, it was split into the train (75%) and test data (25%) for Model 2 into the train (48%), validation (32%), and test data (25%). The churn percentage in the Model 1 dataset was 8% on train and test data. Whereas for Model 2, churn was 17%, 25%, and 31% for training, validation, and test data, respectively.

The oversampling technique SMOTE NC (Chawla et al., 2002) was applied to the training datasets to improve predictive performance by balancing the instances in each class. The validation and test datasets maintained the original distribution to assess the models' performance, presenting a natural distribution of churners. Furthermore, the original and oversampled training data were relied on to build models based on state-of-the-art algorithms XGBoost and LightGBM. Moreover, RF and DT models were also constructed for performance comparison. For the algorithms developed on top of the original training data distribution, the parameter class_weight was set to balance.

These algorithms have several parameters that can be used to optimise the models' performance and reduce the overfitting effect on training data. Thus, a grid search with 3-fold cross-validation was computed for each algorithm and training dataset combination with the parameters defined in Table 3. To select the optimal parameter combination, the averages of multiple evaluation metrics (accuracy, balanced accuracy, precision, recall, F1, and Area Under the Curve (AUC)) were extracted from the grid search, and the five models with the highest averages on each metric were considered, producing 360 different models (5 (top 5) × 6 (evaluation metrics) × 4 (algorithms) × 2 (datasets)). These were evaluated against the test and validation datasets, enabling the parameter selection for each dataset distribution and algorithm with the highest F1 and AUC. The results of this selection are detailed in the Results section. Finally, Model 1 and Model 2 were selected based on the highest F1 and AUC. F1 is a metric that combines precision and recall. It is a favoured metric when dealing with class imbalance problems. Moreover, AUC considers sensitivity and specificity as individual class performance metrics over all possible thresholds.

Evaluation and deployment

Two consecutive experiments were conducted, one for each model, involving daily churn predictions, categorising subscribers with a predicted probability to churn over 50% as "probable churners". A/B testing was performed in both experiments, where 50% of the

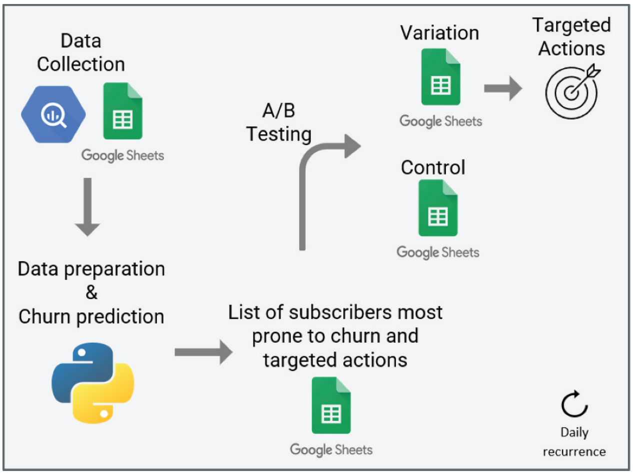


Figure 2. Daily predictions pipeline.

"probable churners" were sampled to the verification group (group to be targeted with a retention campaign), and the remaining 50% were sampled to the control group (no action was taken). Figure 2 represents the framework used in both experiments.

Model 1

The experiment to evaluate Model 1 was implemented over a period of three weeks in September 2021, where daily churn predictions were performed on recurrent and non-recurrent end subscribers. The retention measure of the first experiment was to offer one month of free subscriptions for subscribers who purchased an annual subscription.

Model 2

A second experiment was tested in April 2022 to evaluate Model 2, where daily churn predictions were conducted on non-recurrent subscriptions. Having already analysed Model 1 results, it was decided to act on "probable churners" through two channels: a newsletter containing content about the Ukrainian war and a phone call (when a phone number was available) with a more personalised approach.

Results

Models selection

The models attained with the grid-search parameter selection resulted in eight possible modelling options for both modelling contexts. The evaluation metrics presented in Table 4 indicate that:

- For recurrent and non-recurrent subscriptions (Model 1), DT and RF present the lowest performance considering the F1 in contrast with LightGBM and XGBoost. However, only XGBoost built with the non-balanced dataset does not overfit the training data.

Table 4. Evaluation metrics of models trained with original and balanced data for both modelling contexts.

		Accuracy		Balanced Accuracy		Precision		Recall		F1		AUC		Specificity	
	Algorithm_dataset	Train	Validation (Val)	Train	Val	Train	Val	Train	Val	Train	Val	Train	Val	Train	Val
Model 1	DT_original	94.52%	94.58%	82.09%	82.65%	68.34%	64.32%	67.08%	68.52%	67.71%	66.35%	90.56%	91.86%	97.09%	96.78%
	DT_smote	82.45%	94.57%	82.45%	82.54%	95.94%	64.31%	67.77%	68.28%	79.43%	66.24%	91.90%	91.83%	97.13%	96.79%
	RF_original	92.97%	93.28%	91.42%	89.43%	55.55%	54.47%	89.54%	84.87%	68.57%	66.35%	98.00%	96.45%	93.30%	93.99%
	RF_smote	93.31%	92.24%	93.31%	88.92%	92.84%	50.18%	93.85%	84.99%	93.34%	63.10%	98.63%	95.73%	92.76%	92.85%
	LGB_original	99.48%	96.08%	99.71%	87.84%	94.24%	73.38%	100.00%	78.09%	97.03%	75.66%	100.00%	95.22%	99.43%	97.60%
	LGB_smote	94.20%	92.55%	94.20%	88.26%	93.63%	51.42%	94.85%	83.17%	94.24%	63.55%	98.67%	95.64%	93.55%	93.35%
	XGB_original	**95.10%**	**95.15%**	**91.92%**	**88.67%**	**66.04%**	**65.27%**	**88.07%**	**80.99%**	**75.48%**	**72.29%**	**98.38%**	**96.10%**	**95.76%**	**96.35%**
	XGB_smote	98.10%	92.52%	98.10%	85.47%	98.16%	51.41%	98.04%	77.12%	98.10%	61.69%	99.81%	93.13%	98.16%	93.83%
Model 2	DT_original	93.60%	91.02%	93.89%	91.03%	75.15%	76.80%	94.32%	91.05%	83.65%	83.32%	98.62%	95.41%	93.45%	91.01%
	DT_smote	88.75%	89.78%	88.75%	86.87%	92.31%	78.20%	84.54%	81.14%	88.26%	79.64%	92.80%	91.97%	92.96%	92.61%
	RF_original	95.10%	92.73%	93.63%	92.35%	82.33%	81.28%	91.37%	91.61%	86.62%	86.13%	98.82%	97.59%	95.89%	93.10%
	RF_smote	88.66%	91.97%	88.66%	89.45%	94.89%	83.16%	81.71%	84.49%	87.81%	83.82%	97.06%	96.22%	95.60%	94.41%
	LGB_original	94.66%	92.44%	93.90%	92.59%	79.75%	79.75%	92.73%	92.89%	85.75%	85.82%	98.85%	97.71%	95.06%	92.29%
	LGB_smote	94.84%	91.79%	94.84%	91.51%	94.54%	78.92%	95.19%	90.97%	94.86%	84.52%	98.94%	97.47%	94.50%	92.06%
	XGB_original	**95.64%**	**93.70%**	**93.21%**	**92.62%**	**85.96%**	**84.92%**	**89.48%**	**90.49%**	**87.69%**	**87.62%**	**98.81%**	**97.69%**	**96.93%**	**94.75%**
	XGB_smote	95.31%	92.04%	95.31%	91.71%	94.81%	79.59%	95.87%	91.05%	95.34%	84.94%	99.13%	97.65%	94.76%	92.37%

Table 5. Evaluation metrics from selected models.

Model	Dataset	Accuracy	Balanced Accuracy	Precision	Recall	F1	AUC	Specificity
1	Train	95.10%	91.92%	66.04%	88.07%	75.48%	98.38%	95.76%
	Test	95.15%	88.67%	65.27%	80.99%	72.29%	96.10%	96.35%
2	Train	95.64%	93.21%	85.96%	89.48%	87.69%	98.81%	96.93%
	Validation	93.70%	92.62%	84.92%	90.49%	87.62%	97.69%	94.75%
	Test	93.64%	92.57%	82.45%	90.64%	86.35%	98.34%	94.49%

- For non-recurrent subscriptions (Model 2), the F1 measure increases on all algorithms and shows a good generalisation when predicting unseen data. The eight models present a similar performance, and XGBoost trained with the original dataset has the highest F1 performance.
- The models trained with balanced datasets overfit the train data for both modelling contexts.

Therefore, considering F1 and AUC, the selected models were the XGBoost trained on the original dataset distributions. Model 1 attained an F1 of 76% for the training dataset and 72% for the test data (see Table 5). As for the AUC, the results were 98% and 96%, respectively. When considering Model 2, the evaluation metrics were 88% for train and validation data, 86% for test data for the F1, and 99%, 98%, and 98% for the AUC.

Models interpretation

XGBoost allows the analysis of each feature's importance in terms of its weight, gain, and cover. However, for each measure, features could have different importance. Furthermore, SHAP values ensure consistent and accurate results, allowing for a more appropriate interpretation of the features' importance (Lundberg & Lee, 2017). Moreover, tree SHAP extends the evaluation of features' importance by identifying how much impact each feature has on the model's output for individual instances. SHAP's summary plot shows features vertically sorted from most to least important across all data samples, and their impact on the instance's outcome can be analysed horizontally. The colour of each data point denotes the true value of the feature. The main reader subscription retention drivers and their impact are presented in Figure 3 and elaborated on in the following paragraphs.

In both models, the predictors show a similar effect on churn likelihood and share a similar importance ranking in churn prediction. The two predictors with the highest impact on churn prediction are the fidelity_rate (percentage of days with an active subscription since the first subscription date) and the total amount of subscriptions purchased (all_subscriptions). Furthermore, higher values (higher percentage of days with active subscriptions and higher number of subscriptions purchased) for both features are related to a lower propensity to churn. This fact shows that brand loyalty metrics are a good indicator of churn probability, which is consistent with what previous authors have found (Ribeiro et al., 2022).

Moreover, the third most important predictor differs between models: in the first model, it is the current subscription length (in days) (SUBSCRIPTION_ORIGINAL_DAYS); in

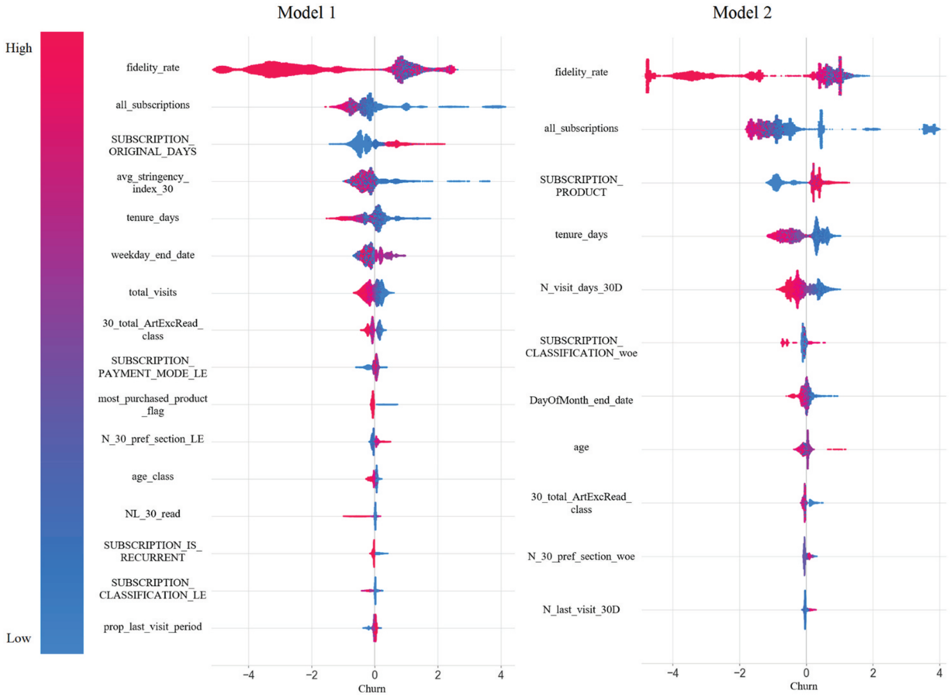
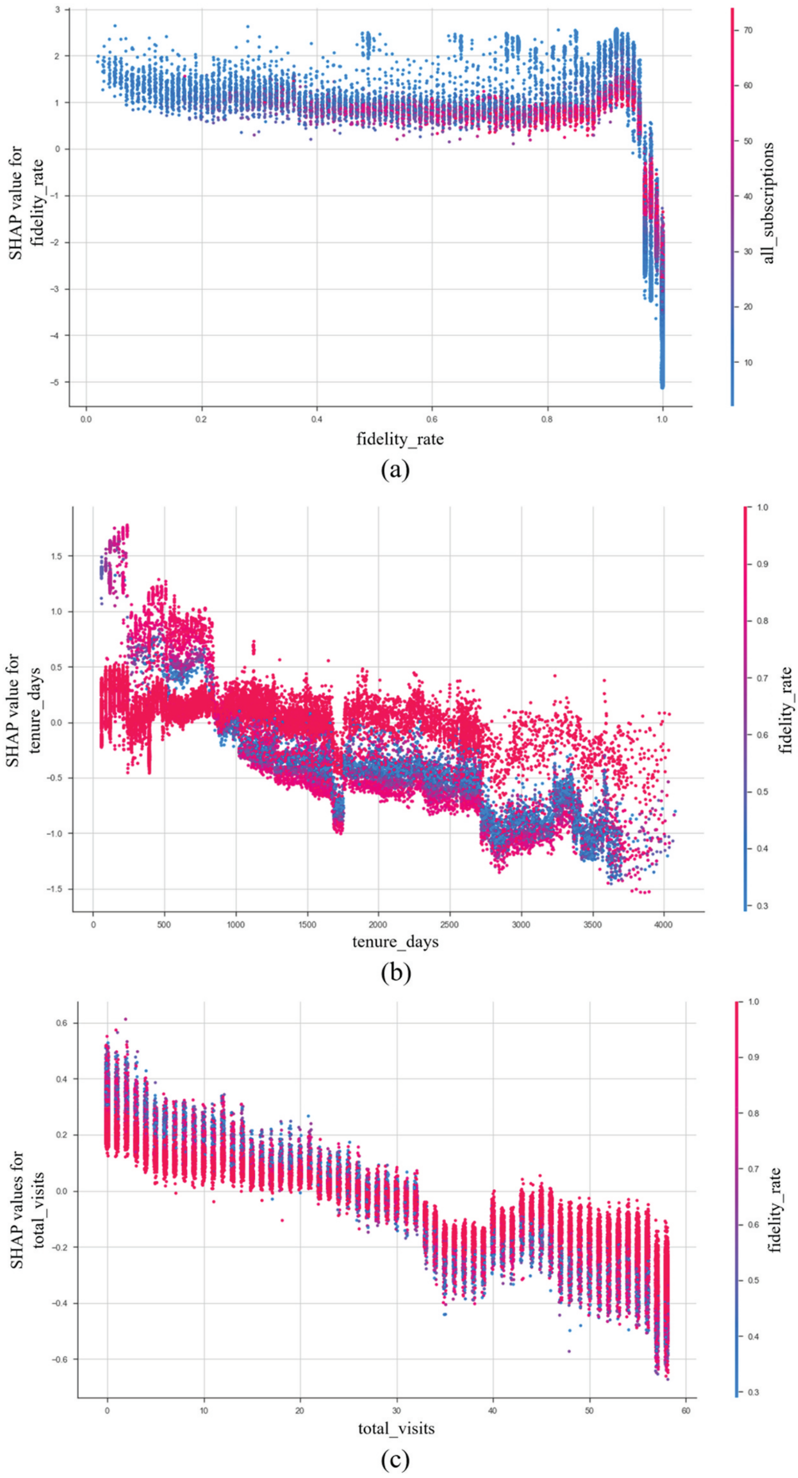


Figure 3. Features importance ranking by SHAP values.

the second one, it is the current subscription product (monthly, annual, and larger, or in between) (SUBSCRIPTION_PRODUCT). Although both features are on different scales, they represent similar information: subscriptions with one year duration present a higher propensity to churn, whereas monthly subscriptions are more related to a lower likelihood to churn. Those findings are also supported by the industry literature that mentions subscription fatigue as one reason for churn (Guaglione, 2021). Readers argue that the reduced reading time does not justify committing to a lengthy subscription. Furthermore, the increase in subscription options across the industry leads the reader to buy shorter subscriptions (Felps, 2022).

Finally, another feature where the difference in the churn likelihood is evident in both models is the total number of days the subscriber visited the website during the last subscription's month(s) (N_visit_days_30D). More days with visits are related to a lower likelihood of churn. This result is aligned with what was already known by the industry. According to the examples presented at the INMA Digital Subscriber Retention Master Class (2022), readers who visit the site daily have less propensity to churn. Furthermore, editorial newsletters are a way to increase engagement and reduce churn (Haggins & Felps, 2022).

SHAP dependency plots help understand the effect of individual features over predictions (see Figure 4). For example, from Figure 4(a), it is visible that subscribers who have almost always had an active subscription since their first subscription (96% fidelity_rate) are less likely to churn. In addition, Figure 4(b) shows a downward trend in the propensity to churn as the days since the first subscription (tenure_days) increase, having



(a)

(b)

(c)

Figure 4. SHAP dependency plots extracted from some model 1 predictors.

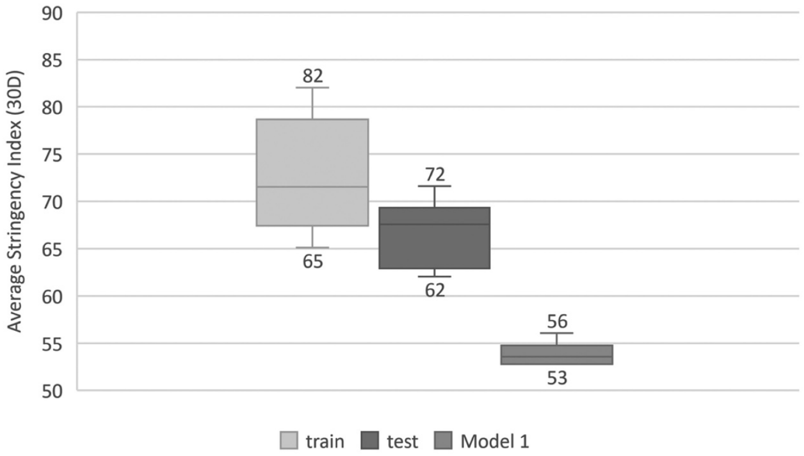


Figure 5. Average stringency index per dataset.

a turnover moment of around 2.5 years, most visible for a group of subscriptions. The same trend is portrayed in Figure 4(c). As the total days with visits during the last two months of the subscription increase, the churn likelihood decreases, with a turnover of around 25 days with visits in the last 60 days of the current subscription.

A/B tests evaluation

Model 1

Model 1 was applied to 4,376 subscriptions, of which 1,003 (20%) were considered "probable churners". From those, 501 (50%) were allocated to the verification group and were impacted by the retention campaign. Model 1 predicted a higher percentage of churn by ten percentage points (pp) in the evaluation group than it predicted when training and testing the model. Furthermore, the F1 considering only the control group and users predicted as non-churners was 14.5%, which indicates that the model predicted poorly. Moreover, considering all users predicted as non-churners and the variation group, the F1 was 16%, which indicates that most of the predictions defined as churners were, in fact, non-churners. However, these results do not directly indicate that the retention action was successful, as the control group's results were much lower than expected.

Two main out of our control facts negatively impacted the model results. In this model, the stringency index was the fourth most important predictor. During the experiment period, the index was lower than the values considered in the model due to a decrease in Covid restrictive measures (see Figure 5). On the other hand, the marketing team implemented a competitive marketing campaign across the website that induced churn. Readers were invited to subscribe to an annual subscription with three months of free content, exclusive for new joiners. However, the retention campaign pushed during the experiment offered one month for a yearly subscription to the high-propensity churners. This induced subscribers to churn and subscribe as new joiners (i.e. new registered readers). Competing against a

Table 6. Retention actions results for model 2.

	Actions			
Group	Newsletter	Phone Call	Active	Churn
Variation	not open NL	no phone answer	2	18
		no phone	28	36
		phone answer	20	24
	open NL	phone answer	4	8
		no phone answer	3	7
		no phone	22	21
control	No Action		86	108
non churner			804	95

better offer than the one being pushed and monitored for the experiment resulted in biased results.

Lastly, the model's training was 30 days prior to the churn moment (last subscription day). However, to impact customers with the retention campaign before the end of the current subscription, for the experiment period, predictions were carried out 37 days before the churn moment (seven days before the subscription's end day).

Model 2

The average stringency index was removed to avoid the challenges faced during the first experiment, and predictions were computed for the 30 days before the churn moment.

During its evaluation period, Model 2 was applied to 1,286 subscriptions (see Table 6), with a forecasted churn rate of 30%. Of the subscribers predicted as "probable churners", 193 (50%) were targeted with the retention actions (verification group). From those, 114 churned. As for the control group (194 subscribers), 108 subscribers cancelled their subscriptions. This difference means that a higher percentage (59%) of subscribers cancelled when targeted with the retention actions compared to subscribers who were not targeted by a campaign (56%). Nonetheless, this is not a significant difference X^2 (1, $N = 387$) = 0.46, $p = .5$) to corroborate that it is better not to contact customers who are ending their subscriptions.

Only 65 subscribers opened the re-engagement newsletter; of those, 45% renewed their subscription, whereas 39% did not open the newsletter, not presenting a significant difference between samples based on the chi-squared test X^2 (1, $N = 193$) = .54, $p = .46$). Conversely, 86 subscribers from the variation group were contacted via mobile phone. Of those, 56 answered the phone, resulting in 43% renewing their subscription. In contrast, only 17% of subscribers who did not answer the phone call renewed their subscriptions. Only 20% of subscribers without an associated phone number, thus not contacted via phone, renewed their subscriptions. These results indicate that a phone call action is significantly more successful.

Discussion and conclusions

Following a long period of a downward trend in newspapers' readership, newspapers have been increasingly adopting digital business models. Compared to other online services, publishers face subscription fatigue and churn increase. Nevertheless, the number of online newspaper subscribers has been increasing over the years. During the past two years, the COVID-19 pandemic and the Ukrainian war have contributed to an increase in subscriptions (Newman et al., 2021).

PÚBLICO newspaper follows the market trends, increasing subscribers and churn. In light of this dual challenge, it was decided to build a model to predict probable churning subscribers. This type of model is beneficial not only to identify churners but also to identify factors that drive churn, allowing the implementation of preventive and engagement measures (Fernandes et al., 2023). Two models were built and tested to attain the objective mentioned above. One model (Model 1) contains all subscriptions, and a second (Model 2) contains only non-recurring subscriptions. Models were evaluated using A/B tests in different periods, applying different retention strategies. Results show the percentage of days with an active subscription (fidelity_rate), the total amount of subscriptions purchased (all_subscriptions), the current subscription length (SUBSCRIPTION_ORIGINAL_DAYS), the current subscription product (SUBSCRIPTION_PRODUCT), and the total number of days the subscriber visited the website during the last subscription's month(s) (N_visit_days_30D) are the top churn predictors.

Our study is very relevant for online newspapers as it unequivocally shows that:

(1) Contacting probable churning customers via a phone is significantly more effective in maintaining subscribers than sending a newsletter or not doing any action (43%, 66%, and 55% churn on each action, respectively). Subscribers contacted with a more direct retention action (personalised phone call) are more likely to renew their subscriptions.
(2) Churn subscription models can be an excellent cost-saving tool by identifying "probable churns". Publishers can create actions to reduce churn and act only on high-propensity churners. One derived result of this model is the ability to forecast the number of cancellations, thus allowing newspapers to better plan their retention and attraction campaigns.
(3) Subscribers with lower fidelity rates and few subscriptions presented a higher propensity to cancel their subscriptions. These findings are consistent with the work of Campbell (2018) and reinforce the need for publishers to consider tailored strategies to address the needs of this subscriber segment in order to straighten their value perception and desire to maintain their subscription.
(4) While product usage variables were not found to be the most critical variables for churn prediction, our findings align with what was found in the literature (American Press Institute, 2018; Financial Times, n.d.; Veseling, 2018), where higher product usage is related to lower churn. This finding reinforces the need for publishers to create engaging content to keep readers' visits high over time. The insight on the number of days with visits in the last two subscription months supported PÚBLICO's decision to apply an automated content newsletter further to impact users who had less than 42% of days active.
(5) Newspapers should consider the over-coverage of a topic, as it can provoke the well-known "news fatigue", thus leading people to bypass news consumption (Fitzpatrick, 2022). In our study, this can be extrapolated from the importance of the stringency index in Model 1, which relates lower stringency values to higher churn probabilities.

(6) A/B testing is a powerful tool to evaluate actions that result from prediction models, thus showing that A/B tests one more way for newspapers to follow other industries in becoming more data-driven in their decision-making.
(7) A/B tests' results in experiment 2 could have been more representative if more subscribers had a phone registered in their account. The good results achieved by calling "probable churners" show the relevance of newspapers to maintaining a complete and updated record of all subscribers.

In terms of theoretical implications, this study is also very relevant to the scientific community by filling a gap in the literature and providing the main engagement drivers to churn (Fernandes et al., 2023). We demonstrated that it is possible to successfully build online news media subscription churn prediction models and identify the factors that drive subscription cancellation. Researchers or analytical professionals could follow the steps described in our study to replicate, extend, or adapt these models in newspapers and other industries that employ online subscription business models.

Despite its benefits and contributions, this study still faced some limitations that future studies could improve. The statistical significance of experiment 2 could have been higher if more subscribers had a phone registered in their account. In future studies, newspapers should make an effort to update their subscribers' database prior to any empirical evaluation. PÚBLICO had limited indicators of website engagement that could improve prediction performance and provide an understanding of the churn decision, such as preferred access channel, most used device, time on website/app, interactions with the customer via the call centre, and purchase channel. Future studies could use the previously mentioned indicators to improve churn models. In addition, employing news content-related variables, such as keywords, could be beneficial in implementing personalised retention strategies.

Phone calls done by an agent are costly and require human resources. Future studies could analyse the use of automated phone calls or other automated re-engagement measures. In addition, more retention actions should be tested as a means to implement distinct and personalised actions for customers with different probabilities of churn.

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