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TOPICAL REVIEW

Factors, Predictability, and Explainability of Mobile Telephony Customer Departure in Telecommunications Companies: A Systematic Review of the Literature

DAVID FREIRE[1], DAVID SANTOS MAURICIO SANCHEZ[1], JOSÉ LUIS CASTILLO SEQUERA[2], AND DANIEL FIALLO MONCAYO[3]

[1]Artificial Intelligence Group, Universidad Nacional Mayor de San Marcos, Lima 15081, Peru
[2]Department of Computer Science, Higher Polytechnic School, University of Alcalá, 28801 Alcalá, Spain
[3]Department of Administrative Sciences, University of Guayaquil, Guayaquil 090510, Ecuador

Corresponding author: David Santos Mauricio Sanchez (dmauricios@unmsm.edu.pe)

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ABSTRACT The telecommunications sector has experienced exponential growth since the year 2000, reaching 5.31 trillion users by 2022, generating $1.07 trillion in revenue for telecommunications companies. However, this growth leads to intense competition among companies for customer acquisition, often resulting in customer churn or switching between telecommunications providers due to the services or experiences received by users. At the moment, algorithms are being developed for churn prediction to assist in taking actions to prevent customer defection. Nevertheless, there is no comprehensive inventory of churn factors or a list of algorithms that explain the reasons for customer churn, despite the existence of numerous factors influencing user retention or defection. This highlights the importance of our work in allowing us to know in advance which client will be a deserter (churn). The purpose of this research is to identify how factors intervene in the customer churn process in telecommunications companies, as well as to list existing techniques for prediction and finally, to present advances in explainability, using a systematic literature review from 2018 to August 2023 using the Scopus and Wos meta-search engines. Regarding the factors contributing to churn, we identified 19 factors encompassing 87 sub-factors, detailed in 87 out of 112 reviewed articles. In terms of prediction, 26 unique algorithm techniques and 16 combinations were identified, presented in 102 out of 112 reviewed articles. Finally, in the realm of explainability, 4 out of 112 articles were found, detailing 5 techniques that help identify why an algorithm selects a customer as potential defector.

INDEX TERMS Churn, telecommunications, prediction, machine learning, explainability, literature review.

I. INTRODUCTION

The telecommunications sector boasts 5.31 trillion users up to 2022, generating an annual revenue of 1.07 trillion dollars [59]. In addition to this growth, structural transformations have occurred, dividing services into mobile (voice and data) and fixed [81]. The mobile phone service has experienced exponential evolution, becoming one of the primary industries in developed countries, with a growing number of phone operators [5] and customers [33] and it even has an attractive projection towards 2030, which will make it go up to 6.3 trillion users, and $1.20 trillion [59]. Furthermore, the number of mobile phone service subscriptions has been increasing since the year 2000, reaching 105 subscriptions for every 100 customers by 2020 [33], that is, there are more subscriptions than people in the world. In this context, there is

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competition for customer acquisition, leading to customer churn, as highlighted in previous studies such as Esteves and Mendes-Moreira [50].

In response to the churn generated, Ahmad et al. [5] suggest minimizing this loss through retention and loyalty strategies, for which the factors that cause desertion must be identified [122], a sentiment echoed by Kim et al. [76], who state that acquiring a new customer is 5 times costlier than retaining an existing one.

Another approach is to predict which customer is most likely to churn or change telephone operators [50], for which two methods are mentioned: the proactive and the reactive, where the first identifies those customers in advance who are likely to resign, while the second occurs when the client has already resigned [37]. It should be emphasized that identifying in advance which customer will end the relationship with the company is known as prediction [145] and is based on the use of algorithms to recognize patterns and extract knowledge [60].

Furthermore, churn prediction can be complemented by an explainability process, which indicates the reasons why a client is selected as a possible deserter [142].

Due to this situation, telecommunications operators aim to reduce the churn rate, which is significant due to the considerable loss it causes. For example, América Móvil (AM) reported churn rates in Brazil, Ecuador, Mexico, Colombia, Chile, and Peru of 2.9%, 3.1%, 3.3%, 4%, 4.1%, and 4.6%, respectively, in 2022 [76]. A similar scenario is observed in other mobile phone operators, such as Telefónica Movistar, which in 2020 reported churn rates in Germany, Ukraine, Brazil, and Latin America (Argentina, Chile, Uruguay, Mexico, Venezuela, Peru, Colombia, and Ecuador) of 1.8%, 1.5%, 3.1%, and 3.0%, respectively [128].

Therefore, identifying the factors that contribute to churn, predicting in advance which customers will defect, and explaining why this will happen, all contribute to taking specific measures to reduce customer churn in telecommunications companies (CCTC).

Within the factors of CCTC, quality is highlighted [63], emphasizing that telecommunications companies must maintain service even in critical situations because customers do not tolerate failures or deficiencies [38]. Other examples of factors include price [37], company image [132], customer service [73], billing [1], and the different types of consumption, such as voice [9], data [5], SMS [8], and MMS [49].

Regarding CCTC prediction, authors like Wu et al. [139] use random forest and achieve an accuracy of 95.34% on a dataset of 4,031 records. On the other hand, Nguyen et al. [98] achieved an accuracy of 95.82% using XGBoost, segmenting the data into five parts, with a total of 50,000 records. Similarly, in Fakhar et al. [52] work, combination techniques were employed, using methods such as K-med, Gradient Boosted Trees, Decision Trees, and Deep Learning, obtaining a 94.7% accuracy on a dataset of 5,000 records.

Concerning the explainability of CCTC, authors like Ullah et al. [131] utilized the Layer-wise Relevance Propagation technique to highlight influential features of the data and determine why a specific customer left and what factors caused customers to abandon the service. Similarly, Slof et al. [120] relied on user-emitted texts, and De Bock & De Caigny [46] used a set of spline rules to determine the reason why a customer is selected as a defector.

Due to the abundance of studies on CCTC, state-of-the-art articles are being developed. In Pamina et al. [101], 74 articles were reviewed out of 951 potentials from the period 2000-2018, identifying 52 techniques that included unique and hybrid algorithms and 47 datasets. On the other hand, Sobreiro et al. [121] reviewed 87 articles out of 448 potentials from the period 2000-2020, identifying 60 different types of prediction algorithms; however, only 52 of these works used telecommunications datasets. These mentioned works showcase various techniques and ways to predict CCTC, contributing a list of algorithms, datasets used, as well as accuracy percentages for achieving such predictions. Nevertheless, these studies lack an inventory of factors and explainability techniques, both of which are crucial; the former for prediction and understanding the causes of churn, and the latter for explaining the reasons behind customer defection.

Therefore, the main objective of this study is to conduct a systematic literature review on the factors influencing the customer churn process, as well as the different techniques used to predict customer defection in advance and provide explainability to understand why a customer resigns.

The primary contributions of this article are as follows:

- Provide an overview of CCTC, particularly in terms of factors, prediction, and explainability.
- Offer readers an extensive range of bibliographic references related to customer churn in telecommunications companies, enabling them to identify factors, various prediction techniques, and existing advances in explainability.

This article is organized into five sections. Section II presents the methodology used for the search and selection of articles. Section III covers the analysis of the obtained results. Section IV discusses the findings. Finally, Section V presents the conclusions drawn from the study.

II. RESEARCH METHODOLOGY

In this article, the systematic literature review has followed an adaptation of the Kitchenham procedure [77], carried out by Alban and Mauricio [10] and Arcos-Medina and Mauricio [26], consisting of the following phases:

- Planning: In this phase, research questions are formulated, and a search protocol is established, including sources, the time period, the search string, as well as inclusion and exclusion criteria.
- Development: This phase involves implementing the search protocol, identifying, and selecting primary articles according to the established research questions.

TABLE 1. Database search string.

Database	Search string
Scopus	TITLE-ABS-KEY ((dropout OR desertion OR churn) AND (telco OR telecom*) AND (explicability OR xia OR prediction OR prognos* OR predicting OR forecast OR factor OR cause))
WoS	Results for ("dropout" OR "desertion" OR "churn") AND (telco OR telecom*) AND (explicability OR xia OR prediction OR prognos* OR predicting OR forecast OR factor OR cause) (Topic)

TABLE 2. Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
"Primary" article or review type documents	Documents not related to the telecommunications industry
Documents that answer the research questions	Documents based solely on questionnaires to prove your hypothesis
Journal source type	Pre-publications
Area related to "Engineering" or "Computer science"	Documents that do not use information from the telecommunications operator to demonstrate their hypothesis (questionnaires, interviews)
English and Spanish language	They are aimed at Internet services, cables, and landline telephony.
Articles that present impact factor with quartile	
Limited years 2018 to 2023	

- Reporting: Statistical results are presented, and research questions are addressed in sections III.

A. PLANNING STAGE

This work is designed to address three research questions:

- RQ1: What are the factors that influence CCTC?
- RQ2: What techniques are used for predicting CCTC?
- RQ3: What advances in explainability exist for CCTC?

To address these questions, a search for scientific articles in journals from the period 2018 to 2023 was conducted. This involved applying a systematic search string in the title, abstract, and keywords for Scopus, and topics for Web of Science (WoS). The search string is in Table 1 and the inclusion and exclusion criteria are established in Table 2.

B. DEVELOPMENT AND REPORTING STAGE

During the established search process, primary studies were identified as potential references according to the proposed inclusion and exclusion criteria. Additionally, it was essential to review the content of the selected articles to determine their relevance to CCTC.

In Figure 1, we can visualize how we transitioned from 1086 articles to 130, excluding 956, as described for each stage of the process and the quantity that was refined at each step.

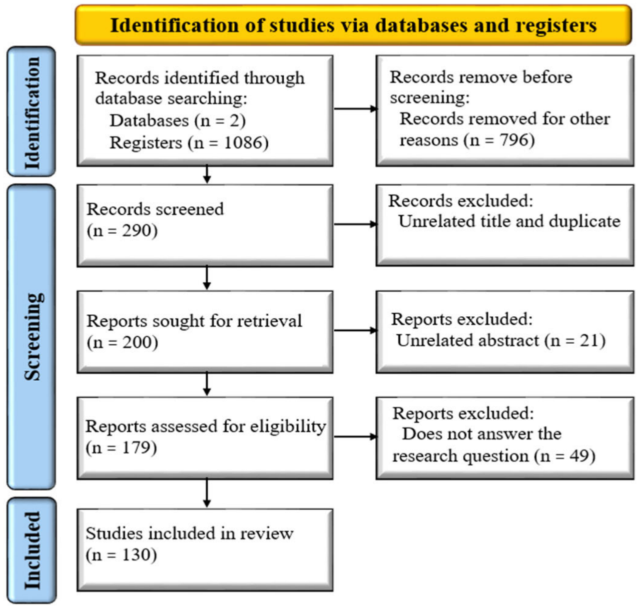

FIGURE 1. Item selection process flow according to PRISMA [147].

TABLE 3. Results of the article selection process flow.

Filters description	Scopus	WoS	Total
Search String	828	258	1086
Language, Journal, Time Period and Field of Study Filter "Engineering" or "Computer Science"	172	118	290
Exclusion of documents that do not address the research questions, are not related to telecommunications, and focus on surveys.	121	90	211
Consolidation of articles and removal of duplicates.			130

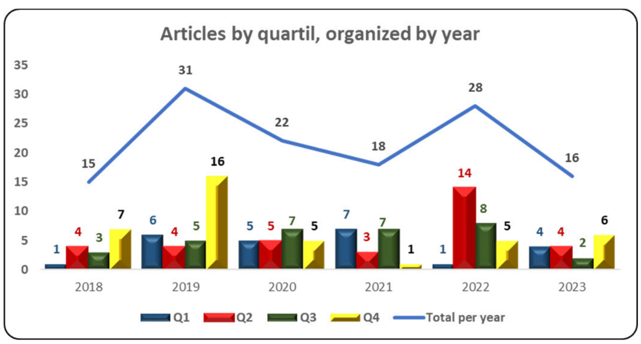

FIGURE 2. Publications - quartiles by year.

In Table 3, the steps for selecting articles can be observed, starting with the application of the search string on Scopus and Web of Science. This resulted in 828 and 258 articles, respectively. Then, different inclusion criteria were applied, resulting in 172 and 118 articles, in that order. Subsequently, filtering was performed based on exclusion criteria, resulting

TABLE 4. Factors associated with the product.

Id	Factor	Subfactor	Articles
F1	Billing	-	[1],[2],[3],[5],[8],[9],[10],[12],[14],[15],[17],[18],[19],[20],[21],[22],[23],[25],[26],[27],[28],[30],[31],[33],[35],[36],[37],[38],[39],[40],[42],[44],[46],[48],[49],[51],[52],[53],[54],[55],[56],[57],[58],[62],[64],[65],[66],[67],[68],[69],[72],[73],[74],[75],[77],[78],[79],[81],[84],[85],[86],[87],[89],[90],[91],[92],[93],[94],[96],[100],[101],[103],[104],[105],[114],[115],[116],[118],[119],[121]
		Night Charges	[14],[15],[17],[18],[20],[21],[23],[27],[28],[30],[35],[36],[39],[44],[54],[66],[73],[77],[81],[84],[90],[94],[115],[116],[118],[119]
F2	Plan	Plan Price	[1],[3],[6],[104]
		International	[5],[14]
		International Plan	[5],[14],[15],[17],[18],[20],[21],[23],[27],[28],[30],[34],[35],[36],[39],[41],[44],[54],[66],[73],[77],[81],[84],[88],[90],[94], [99],[115],[116],[118],[119]
		Service Number	[10],[22],[31],[33],[38],[42],[51],[53],[55],[62],[65],[68],[69],[72],[74],[75], [87],[89],[90],[91],[92],[103],[105],[113]
		Local Plan	[19],[34],[63],[85],[88]
		Product Type	[4],[5],[6]
		Duration	[5]
F3	Devices	Protection	[10],[22],[31],[38],[42],[51],[53],[55], [62],[65],[68],[69],[72],[74],[87],[89], [91],[92],[103],[105]
		-	[9],[12],[14],[26],[37],[57],[58],[74],[75], [100],[101],[114]
		Model	[9],[12],[26],[37],[57],[58],[61],[74],[75], [101],[114]
		Type	[48],[79]
F4	Recharge	-	[8],[9],[12],[25],[26],[37],[56],[57],[58], [67],[74],[75],[101],[114]
F5	Offers	Offers	[9],[12],[26],[37],[46],[56],[57],[58],[61], [67],[85],[93],[101],[114]

TABLE 5. Factors associated with the service.

Id	Factor	Subfactor	Articles
F6	Customer Service	Customer Service	[2],[3],[4],[5],[9],[10],[12],[14],[15],[17],[18],[19],[21],[22],[23],[26],[27],[28],[30],[31],[34],[35],[36],[37],[38],[39],[41],[42],[44],[50],[51],[53],[54],[55],[57],[58],[62],[65],[68],[69],[72],[73],[74],[75], [77],[81],[87],[89],[90],[91],[92],[94],[99],[101],[103],[105], [114],[115],[116],[118],[119]
		Inefficient Relationship Building	[3]
F7	Quality	Call	[2],[3],[5],[9],[12],[19],[26],[37],[48],[57],[58],[78],[86],[100], [101],[114]
		Service	[1],[3],[4],[6],[61],[74],[75]
		Internet	[3],[5],[74],[75]
F8	Service Coverage	Service Coverage	[1],[2],[3],[6],[9],[12],[26],[37], [57],[58],[101],[114]
F9	Complaints	-	[46],[70],[74],[78],[93],[96], [100]
		Resignation Attempt	[4]
		Devices	[74]
F10	Sales Channel	Sales Channel	[74]

in 121 articles in Scopus and 90 in Web of Science. Out of these total articles (290), 50 were discarded for not addressing the research questions, 21 for belonging to other sectors such as transportation, 6 for relying on surveys rather than machine learning (ML) algorithms for prediction, 2 for not being primary sources (state-of-the-art papers), and 81 for being duplicates across both repositories.

In summary, a total of 1086 potential articles on CCTC were identified, of which 130 were selected, representing 11.97% of the total and in the Figure 2 displays the distribution of selected articles by quartiles organized by year, with a trend of publications in Q4 quartile journals and volatility in the number of publications per year.

III. ANALYSIS AND RESULTS

In this section, answers to the 3 research questions posed in section II-A are provided based on the selected articles.

A. RQ1 WHAT FACTORS INFLUENCE CCTC?

The term *factors* refer to the reasons, variables, or causes of customer loss [122]. In this context, 20 factors were identified in 93 studies, classified as follows:

- *Product*: Encompasses everything related to the product acquired by the customer, such as the plan, device, top-ups, and offers.
- *Service:* Refers to the service that the telecommunications company provides, including service quality, coverage, complaints, sales channels, and billing.
- *Customer:* Encompasses information that characterizes the customer, such as age, address, city of residence, social status, profession, number of children, and consumption.
- *External:* Refers to factors external to the service or product offered, such as brand image, advertising, and

TABLE 6. Factors associated with the client.

Id	Factor	Subfactor	Articles
F11	Relationship with the Company	Subscription Time	[4],[9],[10],[12],[14],[15],[17],[18],[19],[20],[21],[22],[23],[25],[26],[27],[28],[30],[31],[33],[34],[35],[36],[37],[38],[39],[40],[41],[42],[44],[46],[51],[52],[53],[54],[55],[57],[58],[61],[62],[65],[66],[68],[69],[72],[73],[74],[75],[77],[81],[84],[86],[87],[88],[89],[90],[91],[92],[94],[101][103],[104],[105],[113],[114],[115],[116],[118],[119],[121]
		Multiples Lines	[9],[10],[12],[19],[22],[26],[31],[33],[34],[37],[38],[42],[51],[53],[55],[57],[58],[62],[65],[68],[69],[72],[74],[75],[78],[79],[87],[89], [91],[92],[101],[103],[105],[113],[114],[121]
		Customer id	[8],[9],[10],[12],[22],[26],[31],[37],[38],[42],[51],[55],[57],[58],[62],[65],[68],[69],[72],[74],[75],[78],[89],[91],[92],[100],[101],[103], [105],[113],[114]
		Status	[14],[15],[17],[18],[20],[21],[23],[27],[28],[35],[36],[41],[44],[54],[61],[66],[73],[77],[78],[81],[84],[90],[115],[116], [118],[119]
		Connections	[10],[22],[25],[31],[33],[38],[42],[51],[53],[55],[62],[65],[68],[69],[72],[87],[89],[91],[92],[103], [105],[113]
		Payment methods	[10],[22],[31],[38],[42],[46],[51], [53],[55],[62],[65],[68],[69],[72], [85],[87],[89],[91],[92],[103],[105]
		Service Usage Type	[29],[50],[74],[75],[78],[96],[121]
		Late Payments	[33],[46],[78],[85],[93],[100]
		Loyalty	[25],[40],[50],[63],[104]
		Transactions, Penalties	[25], [78]
F12	Demography	Area	[9],[12],[14],[15],[17],[18],[19],[20],[21],[23],[26],[27],[28],[34],[35],[36],[37],[41],[44],[46],[54],[57],[58],[61],[66],[73],[74],[75], [77],[79],[81],[84],[90],[93],[100],[101],[114],[115],[116],[118],[119]
		Residential City	[9],[10],[12],[22],[26],[31],[37],[38],[42],[50],[51],[53],[55],[57],[58],[61],[62],[65],[68],[69],[72],[74],[87],[89],[91],[92],[100],[101],[103],[104],[105],[113],[114],[121]
		Gender	[4],[10],[19],[22],[25],[31],[33],[38],[42],[49],[50],[51],[52],[53],[55],[61],[62],[65],[68],[69],[72],[74],[78],[79],[85],[87],[89],[91], [92],[93],[100],[103],[105],[113]
		Dependencies	[10],[12],[22],[31],[38],[42],[51],[53],[55],[62],[65],[68],[69],[72],[87],[89],[91],[92],[103],[105],[113],[114]
		Age	[4],[9],[12],[19],[25],[26],[33],[37],[49],[50],[57],[58],[61],[74],[75], [79],[85],[93],[100],[101],[114]
		Fixed Internet	[10],[22],[31],[42],[51],[52],[53],[55],[62],[65],[68],[69],[72],[87], [91],[92],[103],[105],[113]
		Marital Status	[9],[12],[26],[37],[57],[58],[74],[75],[78],[79],[100], [101],[114]
		Profession	[9],[12],[26],[37],[49],[57],[58],[78],[79],[100],[101],[114]
		Credit	[9],[12],[26],[37],[57],[58],[74],[75],[101],[104],[114]
		Social Status / Travel	[9],[12],[26],[37],[48],[50],[57],[58],[101],[114],[121]
		Children	[9],[12],[19],[26],[37],[57],[58],[74],[75],[101],[114]
		Own vehicle	[9],[12],[26],[37],[57],[58],[74],[75],[101],[114]
		Education	[19],[50],[78],[79],[100]
		Address, Province	[61],[79],[104]
		WirelessUsage, OwnHouse	[78], [79]
		Curiosity	[6]
F13	Voice Consumption	-	[8],[9],[12],[14],[15],[17],[18],[19],[20],[21],[23],[26],[27],[28],[29],[35],[36],[37],[40],[41],[44],[48],[49],[50],[54],[57],[58],[61],[63],[64],[66],[70],[73],[74],[75],[77],[79],[81],[84],[86],[88],[90],[93],[96],[99],[100],[101],[114],[115],[116],[118],[119]
		Voicemal	[8],[12],[14],[15],[17],[18],[20],[21],[23],[27],[28],[30],[34],[35],[36],[39],[41],[44],[54],[66],[73],[77],[79],[81],[84],[88],[90],[93], [94],[99],[114],[115],[116],[118],[119]
		International	[14],[15],[17],[18],[20],[21],[23],[27],[28],[30],[34],[35],[36],[39],[41],[44],[49],[54],[56],[66],[67],[73],[77],81],[84],[88],[90],[94], [99],[115],[116],[118],[119]
		Night	[5],[14],[15],[17],[18],[20],[21],[23],[27],[28],[30],[34],[35],[36],[39],[41],[44],[54],[66],[73],[77],[81],[84],[90],[94],[99],[115], [116],[118],[119]
		Offnet	[8],[9],[12],[26],[37],[40],[48], [57],[58],[63],[64],[85],[96],[100],[101],[114]
		Incoming	[9],[12],[19],[26],[37],[56],[57], [58],[64],[67],[74],[75],[78],[79],[101],[114]
		Roaming	[9],[12],[26],[37],[48],[49],[57], [58],[74],[75],[101],[114]
		Onnet	[8],[49],[63],[64],[70],[85],[88]
		Day	[5],[30],[34],[39],[41],[94]
		Outgoing	[34],[56],[67],[78],[104]
		Overages	[12],[57],[114]
		Fixed	[40],[49]
		Free	[64],[85]
		Charges	[34]
		Incoming and Outgoing Roaming	[48]
		Caller ID, Conferences	[79]
F14	Navigation Consumption	Security	[10],[22],[31],[33],[38],[42],[51], [53],[55],[62],[65],[68],[69],[72],[87],[89],[91],[92],[103],[105],[113]
		Backups	[10],[22],[31],[38],[42],[51],[53], [55],[62],[65],[68],[69],[72],[87],[89],[91],[92],[103],[105]
		-	[5],[8],[19],[38],[40],[48],[50], [61],[63],[70],[74],[75],[79],[89], [93],[96],[100]
		Download, Upload	[56],[67]
		2G, 3G, 4G	[48], [93]
F15	Sms Consumption	-	[8],[48],[49],[61],[64],[70],[74],[75],[93],[96]
		Outgoing, Incoming	[8],[56],[63],[67],[104]
		International, National	[48]
		Offnet, Onnet	[8]
F16	MMS Consumption	Incoming, Outgoing	[56],[67]
		-	[49]

benefits provided by external providers such as television and streaming services.

To identify each factor, an exhaustive review of the 130 selected articles was conducted, identifying two groups: a) Articles identifying factors and b) Prediction articles. The first group contributed all the factors included in each article. In the second group, the factors were given by the variables selected (feature selection) in the prediction process; if the article did not present feature selection, all variables in the dataset used for predicting dropout were considered as factors. It is important to consider that only the variables involved in the churn prediction process were considered, meaning that if the paper excluded variables, these are also omitted in this study. In this way, each paper contributed with one or more factors.

The factors related to the product (see Table 4) specifically focus on what the company offers to the customer, which is a fundamental when studying the reasons why a customer might choose to leave, for example, if the telecommunications company is unable to provide accurate billing information [38], it directly impacts customer satisfaction, potentially causing desertion, which is why this is one of the most studied factors. This factor is present in 81 articles and is studied from different perspectives, such as additional charges, contracted plans, and international charges.

The factors related to the service (see Table 5) specifically focus on the services that the company provides to the customer, which is a fundamental when studying the reasons why a customer might choose to leave, for example, if the Customer Service does not provide the level of support required when the customer has made a complaint [132], it directly impacts customer satisfaction, potentially causing desertion. This is one of the most studied factors, and is present in 61 articles and is studied from different perspectives.

The factors related to the client (see Table 6) focus specifically on the information that characterizes the client with the company, which is a direct source for understanding why they leave. For this reason, this category is the most studied, with 89 articles. For example, *the relationship with the company* is the most important factor, which is present in 80 articles. Another factor studied is *demographic*, which is present in 73 articles, and the factors related to the consumption of services, such as *voice, navigation, sms* and *mms*, which are present in 62, 38, 14, and 3 articles respectively.

In terms of external factors (see Table 7), the external benefit factor is present in 21 articles and includes subfactors such as access to video and TV platforms, as well as benefits unrelated to the service provided by telecommunications operators.

TABLE 7. External factors.

Id	Factor	Subfactor	Articles
F17	External Benefits	Streaming Movies	[10],[22],[31],[38],[42],[51],[53], [55],[62],[65],[68],[69],[72],[87], [89],[91],[92],[103], [105]
		Streaming Tv	[10],[22],[31],[38],[42],[51],[53], [55],[62],[65],[68],[69],[72],[87], [89],[91],[92],[103], [105]
		Benefits	[1],[2]
F18	Company Image	Company Image	[1],[2],[50]
		Advertising	[6]
		Brand	[61]
F19	Deserted Colleagues, Friends, Family	-	[25]
F20	Others	(Others, Month, type)	[8],[9],[12],[19],[25],[26],[29],[33], [37],[46],[48],[57],[58],[74], [75], [78], [88],[93],[101], [114],[121]

B. RQ2 WHAT TECHNIQUES ARE USED FOR PREDICTING CCTC?

Forecasting allows the identification of customers who will terminate their relationship with the company [145]. This could be achieved through algorithms, which can be either individual or hybrid. The latter refers to combinations of algorithms to achieve higher accuracy [60]. We identified 23 individual machine learning algorithms (see Table 8) and 27 hybrid algorithms (see Table 9) in 91 and 27 studies, respectively. Neural networks predominate with 34 articles, where the work by Garimella et al. [57] achieves the highest accuracy at 99.76% on a dataset of 7043 records.

The hybrid algorithm with the highest accuracy, at 99.14% on 71,000 records, is [101] (see Table 9), which is a combination of Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM).

C. RQ3 WHAT ADVANCES IN EXPLAINABILITY EXIST FOR CCTC?

Explainable Artificial Intelligence (XAI) involves the proper interpretation of the prediction process [142], for which models are used to analyze the importance and dependence of factors contributing to explaining the outcome [87]. We have identified five explainability studies (see Table 10).

IV. DISCUSSION

The result of this systematic review is a catalog of factors, prediction techniques, and explainability in CCTC, which will provide researchers with a holistic view contributing to understanding the aspects affecting a customer's retention with a telecommunications operator. Out of the 130 selected articles, we found 93 articles focusing on factors causing CCTC, 5 discussing explainability, and 118 centered on churn prediction algorithms.

Factors influence CCTC, being the causes for customers to tend to leave Telecommunications Companies' services, hence the need to predict and anticipate if this will happen. Therefore, machine learning algorithms are a great alternative to prevent churn in the future. For all these reasons, it is relevant for telecommunications companies to anticipate the causes or factors that particularly affect this undesired outcome with a customer and thus be able to explain the specific reasons for their churn. In this regard, Explainable AI (XAI) is an efficient alternative, whose application will allow for

TABLE 8. Algorithms used for predicting CCTC.

TABLE 8. *(Continued.)* Algorithms used for predicting CCTC.

Id	Algorithm	# Regs.	Acc.	Churn(%)	Art.
1	ANN	51.047	88,12	28,8	[56]
		3.150	98,31	15,7	[66]
		-	90,34	-	[108]
		3.333	91,6	14,49	[2]
		100.000	94,62	49,56	[118]
		20.468	90,9	-	[74]
2	DCNN	7.043	94,8	27	[58]
		7.043	99,76	27	[57]
		212.990	96	5,85	[14]
		18.000	92	8,5	[42]
3	DL (golden sine algorithm)	3.333	98,6	14,49	[3]
4	DNN	3.333	89,44	14,49	[93]
		2.500.000	91,63	-	[88]
		4.914	85,94	-	[99]
5	LSTM	20.000	0,914*	20	[11]
		3.333	95,56	14,49	[105]
		7.043	86,4	27	[27]
6	Adaboost	3.333	96,4	14,49	[110]
7	AdaGrad	3.333	92,6	14,49	[9]
8	ALB (Adaptive logitboost)	4.742	92	-	[62]
9	Decision Tree	3.333	91,7	14,49	[4]
		889	0,831*	31,16	[64]
		-	-	-	[92]
		16.656	58,36	15,12	[47]
10	Bat algorithm	699	99,66	-	[82]
11	Catboost	7.000	81,8	-	[79]
12	Graphs - based representation learning	4.303.541	0,75*	7,8	[95]
13	KNN	7.043	97,78	26,53	[119]
14	PSO	7.042	97,7	-	[54]
		3.333	89,44	14,49	[21]
		7.043	92,4	26,53	[102]
		50.000	96,33	7,93	[137]
		3.333	89,44	14,49	[83]
		7.043	98,1	26,53	[107]
15	Logistic Regression	-	0,856*	-	[89]
		4.126	75	-	[145]
16	Time Series	86.000	88,8	10,9	[100]
17	Random Forest	2.666	97,09	14,49	[109]
		3.333	99	14,49	[48]
		6.679	93,6	13,5	[139]
		64.107	90,2	30	[130]
		7.043	99,7	26,53	[97]
		100.000	62,2	49,52	[49]
		572	87	14,2	[90]
		19.919	73,53	50	[35]
		631.619	62,94	-	[44]
18	CNN	51.047	75,7	7,34	[133]
		7.043	83,4	27	[106]
		100.000	96	14	[15]
		3.333	-	14,5	[111]
19	NN	3.333	86,9	14,49	[45]
		4.250	96	-	[123]
		91.085	68,32	1,83	[43]
		5.000	96,9	14,14	[51]
		200.000	0,71*	9,1	[31]
		1.000	98,61	27,4	[1]
		312	94,82	56,7	[29]
		100.000	73,29	50	[143]
		7.043	80,57	27	[12]
		-	82,12	-	[140]
		-	-	-	[144]
		-	99,5	-	[146]
		3.333	96,43	14,49	[61]
20	Gradiente Boosted	3.333	85,1	14,49	[41]
		50.717	76	12,26	[91]
		-	-	-	[68]
		3.333	95	14,49	[7]
21	XGBoost	51.047	0,66*	28,82	[98]
		3.333	95,54	14,49	[141]
		46.328	95,82	7,93	[28]
		5.000.000	93,3	6	[5]
		7.043	79,8	26,53	[101]
		7.043	79,8	-	[36]
		5.000	95,6	14,14	[16]
		4.000	0,96*	42,5	[18]
		64.107	99,4	30	[125]
		2.000	0,99*	-	[126]
		1.409	81,2	20	[114]
22	Naive Bayes	358	99,99	-	[]
		7.044	84	26,53	[116]
		18.000	0,54*	12,44	[25]
		-	-	-	[20]
		-	98	-	[23]
23	SVM	5.784	77,27	14,49	[24]
		7.044	96,92	-	[86]
		2.000	86,72	20	[96]
		71.047	90	28,82	[103]
		-	97,11	-	[71]
		7.043	95,5	26,53	[124]
		-	-	-	[80]
		51.047	95	28,82	[32]

*: Area under curve (AUC)

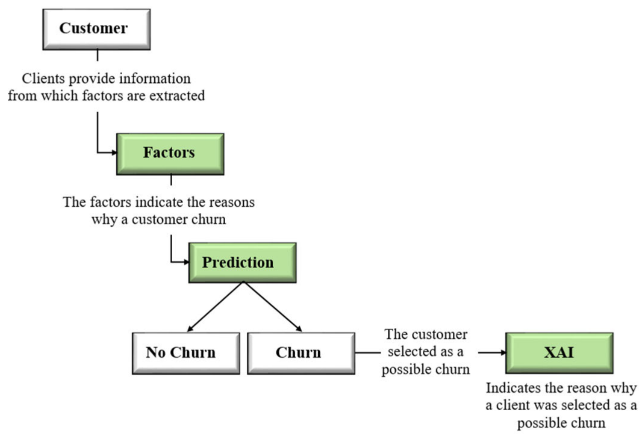

FIGURE 3. Partes del proceso de la CCTC.

explanations to establish strategies that prevent and mitigate potential churn in advance (see Figure 3).

A. ABOUT THE FACTORS OF DESERTION

In this study, 20 factors encompassing 87 subfactors have been identified to help understand the causes of CCTC. In contrast to other state-of-the-art studies, a classification of four dimensions is added: customer (6), product (5), service (5), and external (4), which will allow us to identify which group of factors have the greatest impact on customer churn. The billing factor is the most studied with 81 out of the 93 articles on factors, and it is examined from different perspectives such as night charges, international charges, and additional charges. Another crucial factor is

TABLE 9. Hybrid algorithms used for predicting CCTC.

Id	Algorithm	# Regs.	Acc.	Churn (%)	Art.
1	ACO+RSA	3.333	90,4	14,49	[17]
2	Adaboost + PSO	50.000	0,91*	7,3	[65]
3	C5.0 + Lineal Tree Model	51306	0,67*	1,8	[69]
4	DT+ANN+KNN+RL	53.418	96,9	-	[117]
5	DT+ANN+SVM	1.470	82,3	-	[34]
6	DT+LR+ANN+KNN+NB	5.000	97,6	14,3	[6]
7	DT + LR + FT + RF	5.000	96,6	10,14	[134]
8	DT + LR + RF + SVM	100.304	94,7	50	[13]
9	DT + MLP	272	95,4	-	[30]
10	DT + NB	20.469	70	-	[94]
11	DT+KNN+NB+SVM	3.333	89,4	14,49	[135]
12	DT+KNN+NB+SVM +ANN	100.000	95,1	49,56	[136]
13	Ensemble learning	51.047	-	28,82	[85]
14	Extreme learning machine	3.333	94,6	14,49	[104]
15	Extreme learning machine	-	-	-	[70]
16	GB + DT	51.047	60,7	28,82	[127]
17	Gboost + DT	66.059	0,84*	36,62	[138]
18	K med+GBT+DT+DL	5.000	94,7	14,14	[39]
19	k-medoids+GBT +DT+DL	50.000	93,6	7,93	[84]
20	KNN+Catboost+RF	71.047	86	28,82	[75]
21	LDA + SVM	71.000	99,1	29	[19]
22	PSO + RWN	5.000	96,3	7,6	[53]
23	RF + GB	3.333	97	14,49	[67]
24	RL + MLP	-	-	-	[8]
25	SBM + RF	16.516	73	39,45	[40]
26	Stacked CLV (SCHIE)	3333	88	14,49	[72]
27	SVM + J48	3.333	89	14,49	[112]

TABLE 10. SUDIES on explainability in predicting CCTC.

Id	Technique	Description	Art.
1	Layer-wise Relevance Propagation (LRP)	Heatmaps were used to find which set of features are most relevant in predicting. *Strength*: Significant reduction in the number of features needed for the models, benefiting systems with limited resources. *Weakness*: Slightly lower performance compared to the benchmark methodology.	[131]
2	Spline Rule Ensemble with Sparse Group Lasso Regularization (SRE-SGL)	An interpretable model was obtained taking advantage of the relationship between splines, linear basis functions and rules in the matrix of terms T that share dependence on the same variables. *Strength*: Offers an intermediate solution between the high accuracy of ensemble methods and the need for interpretability in certain contexts. *Weakness*: Model results can be significantly affected by data preprocessing practices such as feature selection and outlier treatment.	[46]
3	Risk model, identifying factors (LDA)	Identify signs of possible churn in textual variables. *Strength*: Provides a 59 churn reasons, offering valuable insights into customer behavior, and classifies them into three categories (controllable, uncontrollable, and unknown). *Weakness*: Aggregating the reasons into three broad categories might oversimplify the diverse factors influencing churn, potentially missing important details.	[120]
4	Clustering based on followers, standard clients, leaders and Core	It uses graph techniques to classify customers, where each customer who churns tells their negative experience to at least one other person, indirectly influencing others. *Strength*: Identifying influencers and their impact on the churn of their neighbors is a significant and practical contribution to churn prediction. *Weakness*: Requires the leader customer to churn first, in order to predict the churn of only the surrounding friend group.	[78]
5	Identification of influence of people external to the client	Determines the level of influence of the clients' friends to make the client change operators. *Strength*: The study covers various aspects of consumer behavior, from adjusting call volumes to changing tariff plans, providing a holistic view of the churn process. *Weakness*: Requires the initial event (influencer churn) to occur to predict the subsequent churn.	[55]

the relationship with the company, with an emphasis on the customer's subscription time with the company. On the other hand, billing and customer subscription time factors allow estimating the telecommunications company's revenues, possibly explaining their importance, surpassing other factors such as customer service consumption.

B. ABOUT ABOUT PREDICTION TECHNIQUES

The study has identified 50 techniques for predicting CCTC, and unlike other state-of-the-art studies, the algorithms are classified into two groups: individual and hybrid. Regarding the first group, 23 algorithms were identified in 91 articles where neural networks predominate, representing 37.36% of the total studies, with the work of Garimella et al. [57] achieving the highest accuracy at 99.76% on a dataset of 7043 records. In the second group, 27 combinations were found in 27 articles, where decision trees were present in several works; however, the combinations differ from each other. Alzubaidi & Al-Shamery's [19] work stands out with 99.14% accuracy on a dataset of 71,000 records.

It is worth noting that the accuracy of the reviewed algorithms differs among articles depending on factors considered, dataset size, churn percentage in the data, data segmentation, and hyperparameter values. All of these represent limitations when comparing algorithm results. In general, it is observed that, hybrid algorithms provide better results than individual algorithms.

C. ON ADVANCES IN EXPLAINABILITY

In this study, five techniques have been identified in five articles, which contribute to the explainability of the CCTC prediction models, which have not been listed in previous states-of-the-art review. Among the techniques found, the following can be mentioned: LRP, SRE–SGL, LDA, Clusters and level of influence. Each of these techniques complements the prediction algorithms, contributing to the explanation of the reasons why the client is selected as a possible deserter. For example, the LRP technique was applied after the prediction made with CNN and created a heat map with which it highlighted the characteristics that have contributed the most to the model's decision. For this reason, a ranking was generated to highlight the importance of the aforementioned.

However, this study detects that there are still few studies that talk about explainability in the CCTC, despite the importance of knowing and explaining the reasons why a client is selected as a possible deserter. Furthermore, we have detected that studies still need to be carried out in which well-known techniques such as LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanation) and FCA (Formal Concept Analysis) predominate.

V. CONCLUSION

This study presents a systematic review of the literature on the different factors and prediction techniques involved in CCTC, in addition to advances regarding the explainability of why a client would be chosen as a possible deserter. This is how 1086 potential articles were identified, of which 130 were selected according to the established inclusion and exclusion criteria. Likewise, three research questions were found aimed at the aspects. In this way, it was clear that CCTC is a topic of interest for the scientific community, given the volume of works found to address the problem in question. This work differs from others because it compiles more up-to-date information that shows the advances in prediction techniques and combinations of algorithms that have been presented in recent years, in addition to the incorporation of factors and explainability techniques that allow the identification of their respective explanation causal for proveer a holistic view of customer churn.

Regarding the factors that influence the CCTC, 20 factors were found that include 87 subfactors, the most studied being billing, since it is present in 87% of the selected articles, in which each author delves deeper looking for the particularity of this to add a different perspective that contributes to knowledge. Regarding the techniques used for the prediction of the CCTC, this work identificated 50 techniques that range from the use of a single algorithm to the combination of several and the incorporation of techniques such as the use of hyper parameters to seek better precision, where the networks neural networks are those with the greatest presence (28.81%) in the selected articles. Regarding the advances on existing explainability for the CCTC, 5 techniques were found that contribute to determining the causes why an algorithm chooses a possible deserter, this is how the LRP technique is the one that best complements by generating a map of heat that visually highlights the characteristics that have contributed most to the decision of the applied model, however, the number of works found is still very low.

This study focuses on the WoS and Scopus repositories, because they are the most relevant in the field of scientific publications on the subject and correspond to the period January 2018 to August 2023, so it could be extended to other repositories and a longer period. Likewise, future research could be focused on the use of machine learning algorithms not yet applied for CCTC prediction and explanation, such as transformer and LIME, respectively.

CONTRIBUTIONS

David Freire contributed to the conception of the study, data collection, and manuscript writing. David Santos Mauricio Sanchez and José Luis Castillo Sequera reviewed and provided support in preparation of the manuscript. Daniel Fiallo contributed to the development of the factor stable. All authors equally reviewed the manuscript and approved the final version.

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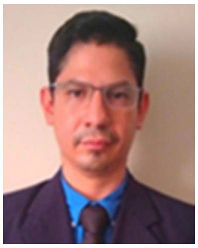

DAVID FREIRE received the degree in computer systems engineering from the University of Guayaquil, Ecuador, and the master's degree from the Escuela Superior Politécnica del Litoral, Ecuador. His research interests include customer dropout, data analytics, artificial intelligence, machine learning, and data mining.

DAVID SANTOS MAURICIO SANCHEZ received the bachelor's degree in computer science from the Universidad Nacional Mayor de San Marcos, and the master's degree in applied mathematics and the Ph.D. degree in systems engineering and computer science from the Federal University of Rio de Janeiro, Brazil. He was a Professor with North Fluminense State University, Brazil, from 1994 to 1998. Since 1998, he has been a Professor with the Universidad Nacional Mayor de San Marcos. His research interests include mathematical programming, artificial intelligence, software engineering, and entrepreneurship.

JOSÉ LUIS CASTILLO SEQUERA received the degree in computing from the Universidad Nacional Mayor de San Marcos, Peru, the dual master's degree in computer project management and in university teaching from Spain, and the Ph.D. degree in information systems, documentation, and knowledge from the University of Alcalá, Spain. He is currently a Full Professor with the Department of Computer Science, University of Alcalá. He leads projects of technological innovation oriented to the use of ICTs in university research groups. He has multiple publications at the level of high-level indexed JCR journals and is the author of books and book chapters related to the field of artificial intelligence. His research interests include information retrieval, knowledge extraction and machine learning, data mining, big data, learning, and teaching innovation. His research interests also include business technologies and intelligent technologies for knowledge management with interdisciplinary technologies.

DANIEL FIALLO MONCAYO received the bachelor's degree in systems engineering, the master's degree in business administration, and the Ph.D. degree in public and private planning. With this impressive academic background, he brings a unique blend of analytical rigor, technological expertise, and strategic acumen to the table. His interdisciplinary approach allows him to navigate complex challenges at the intersection of public policy, technology, and business management with innovation and effectiveness, making him an asset in today's dynamic and interconnected world.