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PREDICTIVE ANALYTICS FOR CUSTOMER RETENTION IN BANKING: A FUSION OF MARKETING AND BLOCKCHAIN

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ABSTRACT

Finding ways to utilise analytics to improve retention of clients in the banking sector is the primary goal of this master's project. Both theoretical and practical components make up this work. The theoretical portion addresses managing client relationships from an analytical standpoint, outlining several factors that influence customer retention, discussing predictive modelling of customer attrition, and presenting potential customer retention initiatives. The primary way of gathering data for the empirical portion is a qualitative research approach that involves four semi-structured thematic interviews with the management of the case firm. The primary conclusions show that the organisation's operations have a significant impact on client retention, and analytics will play a bigger part in the banking sector going forward. The findings also indicate that analytics might enhance specific branch or staff analyses, improve client identification, provide more precise data, and facilitate faster and more efficient retention and CRM activities.

Keywords: Predictive Analytics, Customer Retention, CRM, Client Loyalty

1. INTRODUCTION

With an emphasis on the value of retaining customers in the banking sector, this chapter presents the thesis [1]. It draws attention to the increasing use of analytical instruments in relational marketing initiatives and their rising significance in client retention. In order to anticipate client attrition and gain a competitive edge by staying ahead of the curve, banks are developing churn models. By reducing the need to find new, possibly dangerous clients, customer retention enables businesses to concentrate on the requirements and connections of their current clientele. Long-term clients often make larger purchases, are less price sensitive, and recommend businesses, which lowers operating expenses. For banks to thrive in a highly competitive and developed market, they must comprehend and respond to potential changes in consumer behaviour [2]. Because more financial and insurance enterprises are entering the market and because businesses are offering a wider range of goods and services, markets are becoming more open and complicated, and competition is growing. The demand for innovative management of client relationship initiatives has increased as conventional financial services have moved more and more online. Using predictive analytics, businesses may contact harder-to-reach consumers for engagement and acquisition. The majority of banks, however, are not quite aware of the potential that data offers for efficient company administration. Credit analysis is one example of a banking activity that effectively uses analytics to assess consumer behaviour.

2. LITERATURE REVIEW

Analysing data logically to identify causes, important variables, and potential outcomes is known as analytics. It helps improve corporate planning and provides insights into analytics for business [3]. Among the many benefits of data analytics is a deeper comprehension of the company, its surroundings, and its clientele. A key concept for businesses is customer relationship management, which aims to better understand clients and provide targeted clients with more value. According to the technology-focused viewpoint, managing client relationships is the process of storing and analysing vast amounts of data in order to get insights about customers. Customer relationship systems, which come in functioning, logical, and collaborative varieties, assist in managing significant interactions with customers [4].

In order to more effectively address goals and provide the appropriate message to the appropriate customer, analytical client relationship management entails evaluating client data. Businesses may determine where and why departures of clients are happening and learn how to enhance their retention efforts by tracking and evaluating client retention [5].

Given that many businesses lose 50% of their clientele every five years, statistical analysis is crucial for predicting customer churn or defection. Businesses may determine whether and why defections from clients are happening and how to enhance their retention strategies by tracking customer retention across various segments. Because it enables businesses to more effectively target their consumers, learn more about them, and reduce ineffective marketing efforts, client retention is seen to be more advantageous than getting new customers [6].

Figure 1

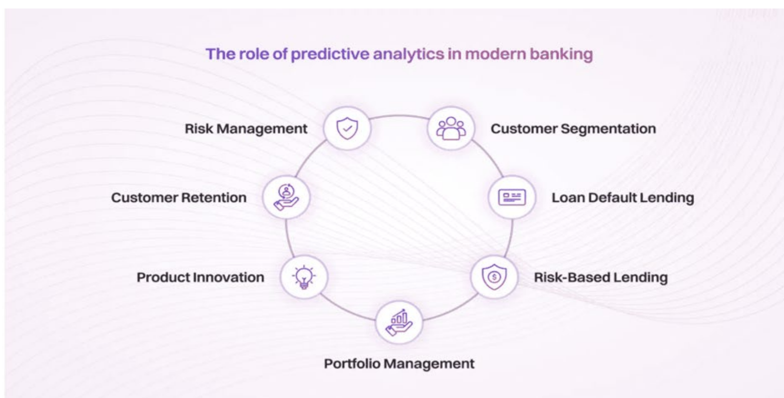

Figure 1 Role of Predictive Analytics in Banking
(**Source:** Ravi, 2021)

Predictive analytics is currently a useful tool for banks that want to improve their customer retention efforts by spotting trends, predicting customer turnover, and coming up with strategies that can be used right away. The concept of client behaviour understanding is supplied by Customer Relationship Management (CRM), and the use of analytics can segment, measure loyalty, and provide quality services [7]. It can be seen that predictive churn models cannot be ignored since the business organization can lose half of its clients in a period of five years. Techniques such as logistic regression can continue to be used when there is a need to interpret results, but machine learning techniques can enhance prediction performance. Retention is always a potential driver of service quality, customer experience, and loyalty [8]. Only recently has blockchain been recognized as a complementary technology, which guarantees the integrity of the data, its security, and the trust of the CRM systems. Together, predictive analytics and blockchain present the banking sector with a powerful instrument in increasing retention within the highly competitive industry.

3. METHODOLOGY

The study follows thematic empirical study design, which involves using mostly secondary data sources to explore the use of predictive analytics to retain customers in the banking industry [9]. The thematic approach was chosen because it would allow defining common patterns, concepts, and themes in a large body of academic literature, industry reports, and case-based evidence. In contrast to quantitative studies that aim at statistical generalisation, this design emphasizes a contextual and interpretative knowledge of the topic. Peer-reviewed journal articles, industry white papers, banking reports, and the current case studies published in the period between 2018 and 2024 are all considered the data sources of this study. These sources appear in some of the most credible databases, such as Scopus, Web of Science, and Google Scholar, which is why they are academically credible [10]. Literature about predictive analytics, customer retention, CRM, and the new role of blockchain in finance were given the most attention. The data were organized and coded in a planned way using theme analysis to get useful information. Two groups of themes were made: customer trust, service quality, churn prediction modelling, and analytics that use blockchain. This method has helped to bring together different points of view and identify key success factors that can be used in modern banks to keep customers. A number of sources were used to associate the results of the research, which is recognised being the method of triangulation [11].

4. ANALYSIS

4.1. ANALYTICS AND CUSTOMER RETENTION:

1) Analytics for business:

The statistical method of business analytics, involving the application of sophisticated quantitative tools to analyse data, is the main topic of this chapter. Analytics is a methodical and thorough procedure that pinpoints specific causes, important variables, and potential outcomes. It is a fact-based process that yields insights and consequences for a company's future action strategy. Frequently measuring and evaluating company performance, diagnosing the underlying causes of issues, and strategically forecasting future projects are just a few of the activities that fall under the umbrella of business analytics [12].

Data analytics, which is closely connected to business analytics, is the process of transforming data and expertise from dispersed data into actionable insights. To get a deeper knowledge of their company and surroundings, companies use statistical analysis to examine important business data. Large databases include individualised and private information, and data analytics aids in the integration and analysis of user data to provide a more thorough understanding of client demands and improve service quality. Additionally, analytics makes it simpler to categorise customers, which enhances customer satisfaction, revenue creation, and fact-based corporate decision-making.

2) CRM, or customer relationship management:

CRM, which aims to comprehend and manage customer behaviour via intentional interactions to enhance the acquisition, retention, and earnings, is an essential component of corporate strategy [13]. Relationship marketing, which encompasses all marketing initiatives meant to create, nurture, and sustain fruitful connections, is where the idea of CRM originated. It is possible to think about CRM as a technology tool, company procedures, strategy, or attitude.

By gathering, storing, and handling customer data, relationship-management systems assist in managing significant connections with clients. These systems treat clients according to their individual requirements, habits, and potential. According to the technologically focused viewpoint, CRM is a procedure that involves storing and analysing vast amounts of data in order to get insights about customers.

Table 1 Methods of Predictive Analytics Used in Banking Retention

Method	Utilization	Advantage
Networks of Neural Systems	Recognizing intricate patterns of retention	High accuracy of predictions
Regression using Logistic	Models for predicting churn	Easy-to-understand results
Random Forests and Decision Trees	Customer segmentation based on turnover risk	Increased precision in aiming

4.2. INTRODUCTION TO THE EMPIRICAL STUDY

In this section, the empirical analysis of customer retention predictive analytics in the banking industry is given on the basis of thematic study of secondary sources. The paper incorporates academic research, industry reports and available banking case studies to assess the role of analytics in customer retention and the role played by blockchain to further improve transparency, security and trust. Customer retention is not a new strategic objective of banks as it has been well understood that cost of acquiring new consumers is significantly higher than customer retention [14]. Predictive analytics provides banks with the opportunity to predict customer churn, optimise relationships, and create interventions. Simultaneously, blockchain is a step toward unlimited storage of information and decentralised trust that can improve customer trust in banking services. The combination of marketing and analytics with blockchain in the framework of contemporary financial services is the focus of the given analysis, which analyses these three dimensions simultaneously. The empirical analysis is themed around three broad areas (1) the use of predictive analytics in business and CRM, (2) what causes customers to stay (loyalty and service quality) and (3) customer churn forecast model and how blockchain can be used to enhance data analytics.

4.3. PREDICTIVE ANALYTICS IN BUSINESS AND CRM

In banking, predictive analytics is the use of complex statistical, computing, and machine learning to analyse bulk customer data to produce actionable information. The two main areas where predictive analytics can be used are business analytics and CRM. On the one hand, analytics can be considered a structured stage of performance measurement and evaluation, problem diagnosis, and forecasting the outcomes in the context of business [15]. In the context of banks, this involves applying transactional, behavioural and demographic data to segment customer, estimate lifetime value and predict the likelihood of churning. With predictive analytics, CRM allows transforming the conventional method of customer management into a data-driven one. Instead of responding to customer complaints or defections, banks are able to intervene before it happens. An example is where the bank can offer special promotions, financial advice or loyalty points to retain a customer where the model is aware the customer is at a high risk of churn [16]. The proactive strategy helps to attain the long run-loyalty and profitability.

To quantify the application of predictive analytics in CRM, logistic regression remains one of the most widely applied statistical models for churn prediction:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}$$

Here, Y=1

Y=1 represents the event of customer churn, and $X1$, $X2$,...,Xn represent predictors such as transaction frequency, service complaints, or account balance trends. This equation demonstrates how statistical weights (β) are estimated to evaluate the likelihood of customer attrition. Banks increasingly complement regression with advanced machine learning models, such as random forests, gradient boosting, and neural networks, which capture non-linear patterns in large datasets and produce higher predictive accuracy [17].

Table 2 Summarises the Commonly Used Predictive Analytics Methods and Their Application in Banking Retention.

Method	Application	Advantages
Logistic Regression	Churn probability estimation	Simplicity, interpretability
Decision Trees/Random Forests	Customer segmentation, risk prediction	High precision, handles complexity
Neural Networks	Detecting complex behavioural patterns	High predictive power, adaptability
Survival Analysis	Estimating time until churn occurs	Useful for longitudinal data

Source: Compiled by Author based on thematic review

The findings from existing empirical studies suggest that combining traditional statistical models with machine learning techniques provides banks with the most robust approach to predicting customer churn.

4.4. FACTORS INFLUENCING CUSTOMER RETENTION

1) Customer Loyalty

Customer loyalty is one of the strongest determinants of retention. Loyal customers not only stay longer but also increase their spending, demonstrate lower sensitivity to price, and provide valuable word-of-mouth referrals. Empirical evidence indicates that loyalty is driven by three primary forms of equity: value equity (perceived worth of banking services), brand equity (reputation and trust in the bank), and relationship equity (the depth of the personal relationship with bank staff and services) [18]. Measuring loyalty typically involves behavioural and attitudinal metrics. Behavioural metrics include repeat transactions, share-of-wallet, and product adoption rates. Attitudinal loyalty, on the other hand, refers to customer commitment, satisfaction, and psychological attachment to the bank. Both dimensions are critical in developing predictive models of retention.

2) Service Quality Perceptions

Service quality is another central determinant of retention. Studies highlight that customers are more likely to remain loyal when service experiences consistently meet or exceed expectations [19]. For retail banks, elements such as speed of transaction, accessibility of digital channels, staff responsiveness, and problem resolution are crucial. Poor service recovery, on the other hand, directly increases the likelihood of churn. An empirical review of banking studies shows that perceived service quality often outweighs pricing advantages in customer decision-making. In this sense, predictive analytics can integrate customer service data, such as complaint logs or service satisfaction surveys, into churn prediction models. This allows banks not only to predict churn but also to understand the root causes driving customer dissatisfaction.

3) Customer Churn Modelling

Churn, definite as the loss of existing clienteles to competitors, is the reverse of retention. As study identifies churn as a dynamic process influenced by multiple variables, including price competition, product innovation, and shifting consumer preferences [20]. Churn modelling involves predicting the probability of defection based on historical behavioural and transactional data. Beyond logistic regression, survival analysis models, such as the Cox proportional hazards model, are frequently used to estimate the time until a customer churns.

$$h(t|X) = h_0(t).e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}$$

Here, $h\ (t|X)$ represents the hazard rate, or risk of churn at time t, given predictors X. This enables banks to assess not just whether a customer will churn but when it is most likely to happen, allowing for timely intervention.

4) Integrating Blockchain into Predictive Analytics

Although predictive analytics provides powerful insights, one of the biggest challenges in banking analytics is data trustworthiness and transparency [21]. Data may be siloed across branches, vulnerable to manipulation, or subject to privacy concerns. This is where blockchain can complement predictive analytics. Blockchain, with its decentralised and immutable ledger system, ensures that customer data cannot be tampered with and is transparently accessible across authorised stakeholders. For predictive analytics, blockchain can:

- **Enhance Data Integrity:** Immutable records prevent manipulation of customer histories, improving the reliability of churn models.
- **Facilitate Secure Data Sharing:** Banks can collaborate with fintech partners or credit agencies on predictive modelling without compromising customer privacy [22].
- **Support Decentralised Identity:** Customers can maintain control of their data, increasing trust in CRM systems and retention initiatives.
- **Enable Real-time Analytics:** Smart contracts can automate retention interventions, such as triggering loyalty rewards when risk thresholds are detected.

An empirical review of blockchain-enabled banking case studies shows that early adopters report improvements in both customer trust and operational efficiency. By combining predictive models with blockchain-based data governance, banks can not only improve the accuracy of retention predictions but also build stronger, trust-based relationships with their customers [23].

4.5. EMPIRICAL SYNTHESIS

The thematic analysis highlights that predictive analytics is most effective when applied in a holistic framework that considers behavioural, attitudinal, and service-quality factors. Advanced modelling approaches provide high accuracy, but their success depends on the quality and integrity of input data. Blockchain provides a potential solution to data integrity and privacy challenges, thereby enhancing the effectiveness of predictive analytics. The findings also indicate that predictive analytics is not a standalone solution. Banks must complement analytics with proactive CRM initiatives, such as personalised engagement, loyalty programs, and responsive service recovery [24].

The integration of blockchain further adds an element of transparency, ensuring that customers trust how their data is used, which in turn reinforces retention. The empirical study demonstrates that predictive analytics offers powerful tools for banks to anticipate churn, segment customers, and tailor retention initiatives. Some of the critical influencing factors such as customer loyalty, perception of service quality, and behavioural patterns, can be measured and modeled using statistical and machine learning methods [25]. The innovation of Blockchain becomes an addition to the existing one and makes customer data relyable and enhance the trust of customers in CRM operations. In summary, predictive analytics and blockchain-based data management can provide banks with a proactive strategy to boost retention, reduce operational expenses, as well as maintain a competitive advantage in an increasingly digitalized financial environment.

5. DISCUSSION

5.1. FACTORS INFLUENCING CUSTOMER RETENTION:

1) Client Loyalty:

The topic of customer loyalty is complicated, and there are differing views on it in the literature. Economic equity, reputation, and relationship equity are its main drivers. Although they may not always display customer interaction behaviour, loyal consumers often return items. Some academics contend that loyalty is synonymous with retention, while others think there is a direct causal relationship between retention and devotion. Businesses may use commitment, rate, and recency to gauge consumer loyalty. Behaviour, attitude, and integration are the three main types of techniques used in loyalty research. Behavioural methods use market share, proportions, and continuity to gauge loyalty. Attitude-based methods assess loyalty by looking at the psychological dedication and involvement of the consumer [26]. Relationships that are genuine are voluntary, but those that are forced are not. Using both aspects, an integrated strategy focuses on consumers' favourable perceptions of providers and their propensity to make repeat purchases.

Figure 2

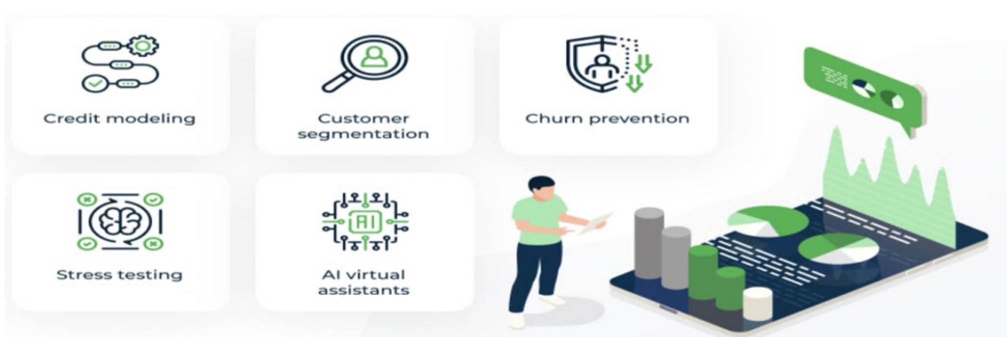

Figure 2 Banking Data Analytics
(**Source:** Yu, et al. 2023)

2) Opinions of service quality:

For banks to retain client loyalty and increase their market share, service quality impressions are essential. They are characterised by the degree of contentment or discontent that consumers have with the process of buying and the use of various service formats. How effectively an organisation's service level meets consumer expectations is an indicator of its service quality. Experiences and recollections influence how customers view relative comparison. When clients assess value, opinions of service quality are more important than price.

Successful plan execution depends on providing excellent customer service, which incorporates a variety of elements from different organisational departments. For retail banks, Levesque and McDougall (1996) place a strong emphasis on client retention and satisfaction. They discovered a scale of factors, such as service attributes, service issues, service recovery, and items utilised, that are associated with opinions of service quality. Inadequate bank service recovery capabilities and other service issues have a big influence on consumer happiness and switching intentions. For banks to be successful, it is crucial to comprehend service needs and how excellent service delivery performance affects client perceptions.

3) Customer churn prediction analytics modelling:

The amount of current customers that choose to go to a different brand or business because of superior options is known as customer churn, loss of talent, turnover, or abandonment. The reverse of client retention is defection, which occurs when consumers stop making recurrent purchases and often move to rivals. Price, service, or good, market, innovation, or organisation is some of the factors that might cause defection. Because connection factors are stronger for loyal consumers than for relatively new ones, the likelihood of customer turnover fluctuates throughout the course of the customer lifecycle [27].

To keep consumers from leaving, every business needs to monitor retention and defection. Businesses that value and foster client loyalty have more success in lowering customer attrition. It is possible to detect churning consumers by tracking the changes in customer behaviour and contrasting recent and historical activity.

Figure 3

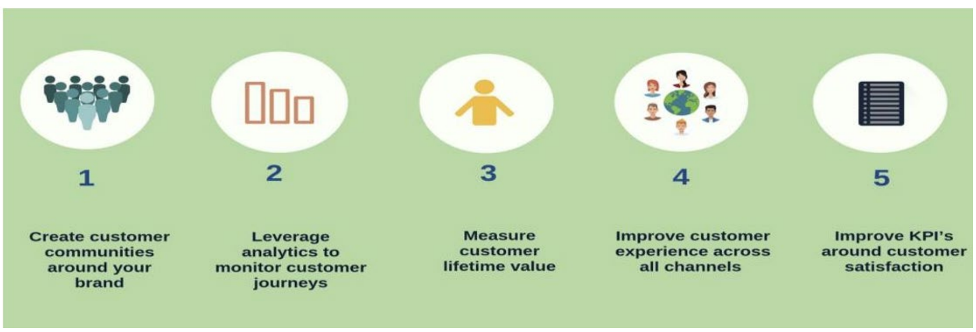

Figure 3: Customer Retention Strategies

(**Source:** Antwi, 2023)

The empirical analysis of predictive analytics and blockchain integration for customer retention in banking has highlighted several important themes. Predictive models help banks anticipate churn and personalise engagement, while blockchain ensures data transparency and integrity, enhancing customer trust. This discussion situates these findings within the broader literature, evaluates their implications for banking practice, and identifies challenges and future opportunities.

5.2. PREDICTIVE ANALYTICS AS A STRATEGIC TOOL

One of the most important insights of the study is the growing role of predictive analytics as a strategic tool in banking. Retaining customers has always been more cost-effective than acquiring new ones, but the intensity of competition in the digital era has made it a necessity rather than an option [27]. Banks are under pressure not only from traditional rivals but also from fintech start-ups, neobanks, and non-financial technology companies entering the financial services space.

Predictive analytics enables banks to respond to this challenge by shifting from reactive to proactive strategies. Instead of waiting for customers to defect, banks can identify churn risks in advance and intervene through targeted offers, loyalty schemes, or improved service delivery. This ability to pre-empt attrition represents a significant competitive advantage. The literature reviewed confirms that organisations that harness predictive analytics achieve greater efficiency in marketing expenditure and stronger long-term customer relationships [28].

From a managerial perspective, predictive analytics transforms decision-making by providing fact-based insights rather than intuition-driven judgements. Managers can rely on churn probability models and customer segmentation analyses to allocate resources more effectively. This aligns with the broader movement in banking towards evidence-based management and digital transformation.

5.3. THE CENTRAL ROLE OF CUSTOMER LOYALTY AND SERVICE QUALITY

The analysis has also underscored that predictive analytics is only as valuable as the behavioural and attitudinal factors it seeks to model. Customer loyalty and perceptions of service quality emerged as decisive factors influencing retention outcomes.

Loyalty cannot be reduced to transactional repetition alone. As research emphasise, it encompasses psychological commitment, emotional attachment, and the perception of value equity [29]. Customers who feel valued and respected are more likely to maintain long-term relationships, even when presented with competitive alternatives. Predictive models that incorporate attitudinal variables alongside behavioural indicators therefore offer more robust predictions.

Similarly, service quality plays a central role in retention. Research shows that customers judge banks not only by product offerings but also by the quality-of-service encounters, whether digital or face-to-face [30]. Service failures, particularly when recovery is poor, have an outsized effect on customer defection. Predictive analytics can help banks monitor service quality through analysis of complaints, feedback surveys, and digital interaction data. In this way, retention becomes not just a matter of offering financial incentives but of ensuring consistently positive service experiences.

5.4. CHURN PREDICTION MODELS AND PRACTICAL APPLICATION

The empirical study highlighted several churn prediction models, ranging from traditional logistic regression to advanced machine learning and survival analysis. Each model has its strengths and limitations. Logistic regression remains popular because it is simple and interpretable, enabling managers to understand the drivers of churn [31]. However, it tends to be inaccurate as compared to machine learning methods.

Neural networks, decision trees, and random forests provide more predictive power because they can identify non-linear, more complex relationships with customer data. These are best applicable in the banking setting where data are large in size and multidimensional. At the same time, they might be complex enough to become less transparent, and interpretability issues will be a concern. Managers might be reluctant to take action based on insights they do not know well, the problem sometimes called the black box problem in artificial intelligence [32].

One more useful concept in survival analysis is that, not only does it predict whether a churn will occur or not, but also approximates the time when it is most probable. This periodicity is an important dimension of the timing of interventions. For example, a bank may understand that certain groups of customers are the most likely to churn within the first six months of opening an account and then provide an early engagement initiative accordingly.

All in all, we can see that a combination model (that is a combination of multiple models) is the best. Furthermore, machine learning can also predict accurately, and managers can use these results to learn from the models and make the most important decision. Triage is successful when survival analysis literally helps them establish timing.

5.5. BLOCKCHAIN AS AN INNOVATION ADD-ON

One thing that makes this work appealing is that the authors put blockchain into the framework of predictive analytics. While data can be used to predict the future, blockchain can be used to create trust in a group of peers. This combination is even more important at a time when data protection is receiving increased attention. Blockchain is a decentralized and unchangeable record-keeping system. This implies that customer data is immutable [33]. There are two implications of this. One is that it also allows the predictive models to be more accurate by ensuring that data is secure. Developing any predictions does not matter what the prediction is for because, at the end of the day the more data there was the more likely it was that a prediction would be correct, but if that data is not being inputted to the system in any way the end result is that the system never works. Blockchain Makes These Risks Lesser. Second, it is about consumer issues in relation to the utilisation of their own personal information. Blockchain gives customers the ability to control their own data through decentralised identity and sharing control. But the increased openness alone can improve retention because the openness builds trust.

In addition, retention activities can be automated via smart contracts on blockchain platforms [34]. A predictive model may set off a loyalty reward or service action automatically by a smart contract when it sees that a customer is at risk. This makes it easy for data to lead to action, which cuts down on delays and improves responsiveness.

Still, there are problems with how blockchain is used as well. It might cost a lot to connect old payment systems. In most places, rules about using blockchain in financial services are still in their early stages of growth. Some systems have also had problems with sustainability because of how much energy blockchain uses. Another useful application of blockchain in prediction analytics is that it can help to provide greater trust and security and empower customers.

5.6. IMPLICATIONS FOR BANKING PRACTICE

The results of the study are really important for everyday life.

For one thing, banks should invest in layering another layer of data on top of existing data. Advanced models are just one part of this. The quality, integration and control of the data are also very important. For analytics to be effective they need a solid foundation of clean, comprehensive and up to date data [35]. Second, analysis of retention should consider both quantitative requirements and more qualitative requirements for retention. Models can help managers determine who is likely to turnover, but they also need to explain why. This includes a good customer experience, good services and programs that keep customers going back for more. Even so, analytics should not be used to make decisions about interactions - it should be used to complement human decision making.

Third, blockchain gives banks a way to improve how they handle customer data and build trust. Using identity verification, blockchain-based data management tools, and automated actions can help banks stand out in a market that is already full [36].

Lastly, the organization's culture is very important. To make analytics and blockchain work, leaders need to back the change, make sure it fits with the overall strategy, and teach the staff what they need to know. If banks don't see predictive analytics as more than just a tech add-on, they won't get all of its benefits. As part of a larger plan for digital change, it needs to be written into the organization's DNA.

5.7. LIMITATIONS AND FUTURE RESEARCH

The thematic empirical method has led to useful information, but it also has some problems. When studies use secondary data, the opinions are based on past studies and papers that don't always show how banking works in real life. Also, predictive analytics using blockchains is a fairly new technology, so there isn't a lot of real-world proof available just yet.

More research could build on this one by using source data, case studies, or interviews with people who work in banking. It would also be helpful to test the suggested combination of analytics and blockchain using numbers. Cross-country or cross-bank model comparative research can also help show how application and success can be different depending on the setting. As it talked about, prediction analytics and blockchain work together to make the banking industry a powerful way to keep customers. Blockchain and predictive models make it possible to identify and deal with customer turnover before it happens. They also help customers trust the database and its data integrity. The main ideas are quality of service, loyalty modelling, and churn modelling. More advanced analytics have given us more correct information. As an example, analytics and blockchain can give a business a long-term edge in a financial world that is always changing.

For banks that want to stay successful in the digital world, marketing, prediction analytics, and blockchain are not just new technologies; they are also important parts of their business strategies.

6. CONCLUSION

One of the many advantages of customer retention management is that it allows a business to focus on its existing customers, rather than trying to acquire new ones. There isn't a lot of writing floating around on the banking industry which combines predictive analytics views and keeping clients. Therefore, to bridge that gap in the literature, the purpose of this study is to provide a comprehensive list of customer retention drivers and activities in the banking business. It also covers a wide variety of data analysis techniques and presents a long list of models for predicting churn developed by big financial institutions. The paper also discusses client retention in the context of small business, and the importance of managing attrition in this type of business.

CONFLICT OF INTERESTS

None.

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