Impact of Claim on Renewal Retention: Relative Influences of Natural or Induced Claim

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This dissertation is dedicated to advancing insurance retention strategies, customer engagement models, and sustainable healthcare finance, with the hope of contributing meaningfully to both scholarly discourse and industry practice.

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Introduction

Every industry allows customers flexibility to either remain loyal or defect to competitive companies, and the insurance industry is no exception. Inability to avert the decline of their client base might adversely affect the company's shareholder value and market share. The Indian health insurance business is in its early developmental phase and is one of the most under-penetrated industries internationally (CRISIL). The choice to stay with the firm may stem from several variables, including as service quality, insurance prices, individual preferences, personal claims experiences, and other considerations (Smith, Willis & Brooks, 2000). Although several aspects may be immutable, firms may mitigate some via initiatives aimed at enhancing client retention procedures. While retention measures may not be infallible (Griffin & Lowenstein, 2001), it is the company's obligation to comprehend the advantages of implementing retention programs. The increased medical requirements and costs associated with the aging demographic, prolonged lifespan, and changing patient expectations, along with technology progress, have led the public to financially safeguard against health-related hazards (Ecer & Pamucar, 2021). The health insurance sector is essential for providing financial stability and facilitating access to excellent treatment for people and families. Nonetheless, like to other sectors, consumer retention poses a considerable issue. Customers often change providers owing to factors like superior cost, enhanced service options, or unhappiness with their existing insurance. This poses both an opportunity and a difficulty for insurers. Organizations that successfully retain consumers will gain a competitive advantage, but those experiencing elevated customer attrition may encounter financial challenges. Furthermore, due to sudden outbreak of COVID-19 pandemic, the people experienced an urgent need for private health insurance policies.

The World Health Organization declared COVID-19 as a pandemic on March 11, 2020. COVID-19 caused several negative outcomes such as disruption of economic activities, disturbance in the employment system, decline of the financial markets and interrupted corporate operations in almost all nations globally. As this was a critical health crisis, people realized the need for having health insurance policies which caused the increasing demand for the holding the health insurance policies. Even the people that did not use to give any consideration to healthcare also became aware with the importance of health insurance policies. As a result of this, the demand for the insurance policies including private insurance policies and government-sponsored insurance policies increased equally. However, the Indian Health Insurance Sector experienced a declining phase, and this showed demand for good technology adaptability and efficient use of the data. Lacking these aspects made the Indian Health Insurance Sector compromised with the sustaining capacities, profitability, augmenting the business volume and securing market share. COVID-19 exposed existing health insurance provisions facing deficiencies and limitations and hence the insurance companies showed prompt responses to launch COVID-19 specific insurance coverage policies, initiating hospitalization services on cashless basis and facilitation of the telemedicine consultancy services. During the pandemic period and in the post pandemic period, expectations of the client from the health insurance provisions also changed significantly. Client showed preference to the insurance companies which were offering all-in-one claim resolutions, wide-ranging insurance coverage and customer assistance in an aggressive manner. Clients expected value-added insurance services during pandemic period covering wider aspects such as mental health, preventative healthcare services and incentives on health and wellness. The insurance companies which embraced the changes according to the changing customer demands gained a strong customer base, and the others faced the issues of client retention. The epidemic expedited digital revolution in the industry. Insurers used technology, ranging from online policy issuing to AI-driven customer assistance, to enhance productivity and customer experience. Organizations who used digital solutions for claims processing, premium payments, and customer inquiries had increased retention rates, as policyholders favored insurers providing smooth and effortless interactions. Thus, client retention strategies, used across several businesses, possess strategic importance in the health insurance industry.

Companies must comprehend the reasons a consumer may decide to abandon their insurance aid in favor of a competitor or to forgo health insurance entirely. According to Stauss and Friege (1999), the customer recapture approach primarily emphasizes restoring relationships with consumers who have definitively terminated their association with the firm. Kumar et al. (2015) found that customer complaints adversely affect the probability of re-acquisition, indicating that more unfavorable experiences with the company lead to less acceptance of win-back offers. In developing win-back plans, organizations must clearly target lost clients. Nonetheless, if organizations can ascertain and anticipate the probable causes of client attrition, significant resources might be preserved or diverted towards other activities. Emphasizing methods for client retention transcends win-back initiatives and may result in cost efficiencies and optimal distribution of marketing resources (Fornell & Wemerfelt, 1987). Reichheld and Sasser (1990) assert that "zero defection" should be the principal objective of service-oriented enterprises, since their findings indicate that decreasing customer defection rates leads to significant improvements in financial performance. Bolton (1998) posits that service-oriented enterprises should proactively learn from their consumers prior to their defection by assessing their existing satisfaction levels. From a financial standpoint, the expense of maintaining current consumers is less than that of gaining new ones (Ahmad & Buttle, 2007). Earlier research endeavored to establish a favorable correlation between client retention and profitability (Dawkins & Reichheld, 1990; Page et al., 1996; Payne & Frow, 1997) Moreover, consumers will choose to remain only if they see a value proposition in maintaining their association with the organization (Reichheld, 1996; Ch. 3). client retention is far more economical than client acquisition. Studies demonstrate that the expense of getting a new client might be quintuple that of keeping an existing one. Customer retention is an essential business strategy for insurers. Insurers gain from sustained income, less marketing expenses, and an enhanced market reputation when policyholders remain with the same business. The client retention rate was gained only through having a clear understanding of the changing client requirements and showing prompt resolving their issues. The companies gained extra benefit of having broadening coverage of the loyal clients who showed self-interest in extending coverage policies. The confidence level clients in particular insurance companies increased, hence they showed increasing interest in holding supplementary policies including family health plans, enhancement of wellness policies and coverage for critical health issues. With these changes, the customer satisfaction level enhanced and even insurers also augmented revenues.

For client retention in the long run, the major requisite for the insurers is to have proactive consumer engagement approaches. The main tactics they can follow are policy renewal reminders instantly, discount policies for the loyal clients and acknowledging the client about the other benefits they can have within their existing policies. For incentivizing customer retention, the insurance companies can offer the customers easy accessibility of their insurance claims and reduction of the administrative constraints in the processing of claims. Development of a well-designed client retention plan can prove equally advantageous for insurance companies and policy holders.

The loyal and devoted clients have a good level of confidence in the insurance companies as they have health coverage assurance fully guaranteed. The loyal clients also recommend to the relatives and family members to avail themselves of the services of same insurers and hence helps to develop the client base further via mouth publicity. The insurers can also have enhanced customer relationship through having a better understanding of customer expectations, improve the quality of services, resolving client queries promptly and clearing the claims easily and conveniently. Technological innovations are bringing rapid transformation in the insurance sector. Insurance companies are embracing new digital technologies and AI assistance for multiple purposes including optimization of insurance claim process, tailored insurance policy services, and enhancement of level of customer service. The interaction between insurance companies and policy holders has changed with the use of multiple technologies including chatbots, predictive analytics and fraud detection process governed through machine learning. Embracing these AI driven technologies enabled insurers to improvise the client experience level and high client retention rate. Other than this, consumer motivation and engagement level is enhanced through the use of mobile applications, new wellness programs and wearable health technologies.

The Indian health insurance sector has had a significant growth of 1.67 times over a decade, from FY 2014-15 to FY 2023-24. In the same timeframe, Stand Alone Health Insurers (SAHI) expanded by a factor of 5.23, General Insurance increased by a factor of 1.78, and Public Sector Undertakings grew by a factor of 1.13. The company's market share in this study has increased significantly by 3.4 times from FY 2014-15 to FY 2023-24, rising from 1.4% to 4.6%. Consequently, the data from this prominent firm constitutes a significant segment of the private health insurance industry.

Policy renewals continue to be a significant source of revenue for insurers. In FY24, renewals constituted 76% of the total business, whereas new acquisitions represented 38%. Hypothetically, a 1% decrease in renewals could lead to a revenue decline of INR 320 crore across the industry, whereas for SAHI (Stand Alone Health Insurance), the decline would be INR 171 crore. These statistics underscore the significance of customer retention strategies for maintaining business growth. As the industry progresses, insurers must prioritize establishing robust relationships with their clients. Delivering value beyond mere coverage, such as wellness programs, digital convenience, and personalized support, will be essential for customer retention and success in a competitive environment.

As health insurance products are not mandated by regulations and are chosen by individuals who appreciate their value, especially in difficult times, the marketing departments of these companies are tasked with developing more effective strategies to attract new customers and retain current ones. The renewal of health insurance transcends mere financial considerations; it constitutes a behavioral process influenced by individual experiences, social dynamics, and institutional factors. Comprehending the reasons behind individuals' policy renewals or cancellations necessitates insights from multiple fields, including behavioral economics, psychology, and marketing.

The Indian healthcare industry is thriving in employment and income creation due to extensive coverage and improved health services (Forbes, 2024). However, due to India's decentralized approach to health insurance penetration across the country, a large chunk of society is deprived of insurance services and is forced to bear the rising healthcare expenditures. According to Statista, in 2021 only 37% of the total Indian population was covered under health insurance policies. With approximately 400 million people without health insurance coverage, who bear the risk of financial drainage from accessing health emergencies services, is a testament for sleek penetration of health insurance.

Furthermore, every Indian is eligible for free services in the public healthcare facilities however, these facilities face insufficient funding issues and lack robust health infrastructure. Although not free, the next best alternative for these folks is to opt for private healthcare services for rapid and timely treatment.

The hedging of financial risk associated with private healthcare system requires private health insurance players who have upped their game in the past few years, in terms of competitive premium pricing and customer renewal strategies. Additionally, the new Indian Income Tax system does not currently give reimbursement of Rs. 80,000 under Section 80D for taxpayers who acquire medical insurance, as was offered under the prior regime. This change increases the risk of customers opting out due to the absence of visible tangible benefits from holding these policies. Consequently, insurance providers are compelled to revise their current customer retention strategies and develop more effective approaches.

In this context, we look at recognizing some of the key pieces of customer retention from the perspective of health insurance. We examine managerially pertinent inquiries regarding the correlation between the customer's claim history, within the framework of pre-existing conditions, and their retention behavior. Additionally, we explore the likelihood of dependent family members buying independent policy, leading to the expansion of the customer base and number of policies. This is done with a view to look at fresh investments in a firm and also to look at long-term return to shareholders and market returns. We seek to give insight into customer retention in the service-oriented industry, by undertaking what, to the best of our knowledge, is the first experimental research employing the insurance policy-holders data of one of India's largest health insurance firms. We provide model-free evidence obtained from the analysis of data of policyholders who have had experience of claim-incidence in comparison to those who did not. Incorporating the 'Regulatory Focus Theory' and 'Nudging Theory', we conducted a quasi-experiment on customers to understand policy renewal behavior when subjected to communications concerning preventive health check-up. The study's conclusions are meant to aid managers in better creation of strategies for maintaining the consumers and minimizing defection rates. Our inquiry concentrates upon the following research questions:

1. What is the perceived value proposition derived from a claim instance in customer retention?
2. Based on behavioral economics, we examine - Does the introduction of an artificially induced claim or claim-like experience influence customers' intentions to renew their health insurance policies? We want to evaluate whether the impact of induced claim has a long-term effect measured in the form of CLV.
3. What is the influence of a claim in advocating for a new policy for dependent family members, thereby resulting into Family CLV (Customer Lifetime Value) as an expansion to the CLV?

What we are studying is why companies should invest and strategize where renewal retention improves? Claims often serve as important moments to strengthen loyalty. Claim instance and its correlation to renewal retention is through model free reference but what to do for those customers who have not had a claim ?.Thats where the large number of customer base exists for health insurer, and these customers want to see value to the premium spent on perceived financial risk. This is the segment which needs to be ring fenced. Inducement of PHC to these customers will encourage them to stay. This is where we see better results and hence the green shoots to lay the groundwork for lasting growth and unwavering customer loyalty.

The remainder of the article is structured as follows: First, we review the existing literature on key theories. Regulatory Focus Theory, Nudge Theory, and Customer Lifetime Value (CLV) and their implications for customer retention. Second, we outline our hypotheses concerning insurance claims, the use of PHC, and Family CLV. Third, we describe the research methodology, including the experimental methods and research techniques employed. Fourth, we test our hypotheses through a quasi-experiment and empirical analysis and present the findings. Next, we discuss the implications of these findings for managers, customers, and regulators. Finally, we conclude with the summary of the study and discussion on promising avenues for future research.

Literature Review

Fenny et al. (2016) performed qualitative research to examine the complexities of challenges encountered by respondents in enrolling in insurance programs. The interviews took place in May and July 2012, including respondents who are now insured, formerly insured, and never insured. The low rate of health policy renewal is affected by sociocultural and systemic variables, such as cultural norms, insufficient social infrastructure, and subpar treatment. However, research indicates that the insurance renewal framework may be influenced by customers' previous satisfaction levels. Agarwal et al. (2023) examined consumers who were re-engaged via company offers. They presented compelling evidence that trust, and customer pleasure are essential factors in client retention. Ahire & Rishipathak (2018) conducted a descriptive study of 200 persons covered by voluntary health insurance to investigate the variables influencing health insurance renewal procedures. The responses were categorized as persons who used insurance benefits via cashless hospitalizations and payment methods and were analyzed using a 5-point Likert scale technique. The data showed that for the policy renewal, the major requisites are increased cost of healthcare services and elevated wealth. When the claim settlement process is simple and easy for the consumers, they prefer to get insurance policy renewal. Supporting this, Bagchi et al. (2024) argued that improved relationship between consumer purchase intention and satisfaction is dependent on multiple factors including risk reduction, awareness about new policies and improved health security.

Their distinctive discovery underscores the significant role of pleasure in the policy renewal choices of insured clients. The current research has examined the significance of interaction options and advantages within the healthcare sector. The significance of client connection in the insurance industry is receiving heightened focus. Barwitz (2020) examined the domain using two choice-based conjoint analyses, introducing quasi-individual pricing to address the significant variation in health insurance costs and to verify the calculations. The clients exhibit increased willingness to pay for the engagement options provided by the insurance providers. Health insurance firms might significantly enhance their development and profit potential by addressing client demands for enhanced contact via a regulatory fit message framing mechanism. Nonetheless, current research has not quantified the financial implications of interaction quality on long-term client retention, a deficiency that this study intends to investigate. This may also affect the perceived utilitarian value that has been shown to strongly influence consumers' ongoing purchasing choices (Liu et al., 2023). This research, however, lacked a comprehensive investigation of the impact of demographic variations on interaction preferences.

A significant deficiency in existing literature is the absence of experimental studies investigating the impact of claim experiences on renewal rates. Contemporary research mostly depends on survey data, which may be affected by recollection bias or social desirability bias. This research seeks to rectify this restriction by empirically examining the influence of prior claim events on policyholder retention. This research provides a paradigm that integrates regulatory focus theory, nudging theory, and Customer Family Value (CFV) to anticipate and explain customer retention behavior. This starts with an examination of the Regulatory Focus Theory, which offers a theoretical basis for comprehending how motivational orientations affect decision-making about insurance retention.

2.1 Regulatory Focus Theory

A multitude of research has focused on psychological theory and self-regulation. In the self-regulation process, people strive to align themselves with their standards, resolves, and objectives. This idea elucidates the factors and magnitude of an individual's achievement in their ambitions.

This research utilizes Higgins' (1997) Regulatory Focus Theory to analyze how the policyholder's claims experience relates to policy renewal and customer retention.

Each person seeks to get advantageous results from their choices; yet the approaches regarding regulatory frameworks and strategy implementation may vary. In this context, an individual may choose between two approaches as delineated by Higgins (1997) in 'Regulatory Focus Theory': Promotion focus, which seeks to elicit pleasurable consumption experiences and achieve positive outcomes; and Prevention focus, which aims to ensure safety and evade painful consumption experiences and negative outcomes. The promotion emphasis contrasts with the preventive focus on the nature of the underlying objectives pursued, the motives of those adopting each focus, and the primary results desired by these individuals (Brockner et al., 2004). The regulatory focus hypothesis emphasizes the variations in motivational orientation among individuals. A person experiences regulatory fit when their desired goal aligns with their regulatory orientation.

In an organizational context, managers may adjust the design of stimuli to enhance regulatory fit between customers' objectives and the methods they use to achieve them (Higgins et al., 2019). Laufer and Jung (2010) performed research to investigate if the implementation of regulatory focus theory in developing product recall messaging would enhance company performance. This technique improved compliance with product recall requests; nevertheless, it also affects future purchasing choices. They note that the advantages of enhanced compliance surpass the little reduction in possible purchasing intentions. Brockner et al. (2004) examined the correlation between regulatory focus theory and the entrepreneurial process, finding that effective idea development necessitates a promotion emphasis, but the due diligence required in concept screening needs a heightened preventive focus. The authors assert that the majority of research on regulatory-focus theory are performed in controlled laboratory settings and that the theory has significant implications for the field of organizational behavior. It would be interesting to examine the integration of regulatory focus theory within the healthcare literature.

Keller and Lehmann's (2008) meta-analysis indicated that health communication messages had more favorable outcomes when the promotion aligned with regulatory emphasis rather than prevention. The research investigates categories of variables influencing reaction, context, message aspects, and individual variations across 85 empirical trials. Their results suggest that the format of health messages is crucial in influencing the attitudes and intentions of the target audience. Ludolph and Schulz (2015), in their systematic review, discovered that the majority of research indicated that the efficacy of health communication is improved across health domains when aligned with regulatory fit. Through a narrative synthesis of 30 research, the authors suggest that the regulatory fit method is promising, since its tailored tactics might significantly enhance the framing of health messages. Kumar et al. (2021) conducted a comparative analysis distinguishing between prevention- and promotion-focused regulatory initiatives regarding the incidence and mortality of Covid-19. Guided by regulatory focus theory, the authors provide a conceptual framework examining the efficacy of several nonpharmaceutical interventions (NPIs) used by governments to mitigate the spread of disease incidence and mortality. The study's compelling findings indicate that interventions aligned with a prevention-focused approach contribute to reducing disease incidence, while those aligned with a promotion-focused approach enhance the nation's ability to respond to medical emergencies and mitigate disease transmission. Zhao and Pechmann (2007) executed two studies involving 1000 teenagers who were exposed to either anti-smoking commercials highlighting social repercussions or control advertisements integrated within a television program. Research indicated that prevention-focused teenagers responded best to negatively framed anti-smoking communications, whereas promotion-focused adolescents were most effectively influenced by favorably framed, persuasive anti-smoking messages. The authors assert that the two ostensibly distinct frameworks, integrated under the regulatory focus theory, are the foundation of their research, whereby their framework emerges from the junction of the message's regulatory emphasis and its framing. Lin and Yeh (2017) conducted an experiment using four categories of health advocacy advertisements, to which 201 participants answered to the questionnaire. Their findings indicated that when the commercial is promotion-oriented, viewers exhibit favorable intents and attitudes when the tagline employs gain framing rather than loss framing. Consequently, they demonstrated that the activation of a brief regulatory emphasis by advertising methods might produce substantial changes in healthcare consumers' intents and attitudes.

While these studies underscore the significance of regulatory orientation in decision-making, less research has explored the interaction between regulatory emphasis, customer satisfaction, and prior claims in influencing policyholder behavior. This research seeks to address this deficiency by integrating RFT into its experimental design. The next section analyses Nudge Theory, which investigates how behavioral interventions might affect decision-making and policyholder retention.

2.2 Nudge Theory

Nudge theory, introduced by Thaler and Sunstein in 2008, is a subset of behavioral economics that emphasizes the subtle promotion of good and desirable human actions. As per this theory, when people see uncertain modifications in alternatives, they intend to make better and improved decisions. With the help of nudge design, consumer choices and decisions can be made autonomously and clearly symbolize that there are some antecedent causes responsible for the particular choices and decisions. The choice architecture is the central phenomenon of this theory under which the design setting design brings direct impact on the outcomes (Thaler & Sunstein, 2008). Its implications are seen in fields like health insurance, public policies and personal finance.

The Nudge theory has significant implications for improving the healthcare habits of individuals and their health outcomes. In this relation, Patel, Volpp, and Asch (2018) also affirmed that in the public health process, using nudges results into delivering substantial healthcare services to the customers. There are multiple stages involved for implementation of nudges in the healthcare sector including, identification of the main possibilities, assessment of health outcomes, practical implementation, alignment with the stakeholders, comparison of efficacy and transmission of findings to scale. Though the use of nudges is more evident in the selection process, which is singular and straightforward, however they also have the use of complicated decision making. The authors also argued that with the use of nudge units, the compliance of the patients with the healthcare regimens with the preventative care tactics can be improved through development of a good alignment between patient preferences and their cognitive biases. Another research by Misawa, Fukuyoshi, and Sengoku (2020) showed that colorectal cancer screening rate has risen with the help of using nudge theory and machine learning as a combined approach. With the integration of the machine learning methodology, the research determined the encouragement of the target people to get this screening process. In this process, using the EAST Framework, the nudging mechanism used four key components including, effortless (E), appealing (A) cost advantage using screening for public health services with specific emphasis on the societal (S) benefits and withing established time (T) to complete the screening in a defined deadline. Chen et al. (2022) affirmed that with the application of the nudge theory and its assessment of leads to improving the patient health outcomes and improving the overall decisions-making.

They claim that the evidence-practice gap in the healthcare system might be markedly reduced with the integration of nudge theory into clinical decision support systems.

Handel (2013) conducted research examining customer inertia within the health insurance market on the problem of adverse selection. To reveal considerable inertia, they used a major alteration in insurance offerings at a huge corporation and applied a choice model that measures risk preferences and projected health hazards. They use these elements to assess the influence of policies in encouraging customers to make better selections by diminishing inertia. Nevertheless, when these enhanced individual decisions were combined, they markedly exacerbated adverse selection, leading to a welfare decline that quadrupled the pre-existing welfare loss attributable to adverse selection.

The current research has shown several benefits of nudge theory in efficiently promoting healthcare services. Despite its many implications, Nudge Theory has seldom been used in the context of health insurance renewal behavior. Furthermore, there is a deficiency in comprehending the long-term efficacy of nudges and if their influence wanes with time, a matter this research will examine.

This compels us to use the theory's ideas to encourage health insurance policyholders to engage in preventative health check-ups, with the objective of assessing if this results in increased customer retention rates. Expanding on this behavioral approach, the following section examines client Lifetime Value (CLV), which offers a financial framework for evaluating the long-term effects of client retention tactics.

2.3 Customer Lifetime Value

"Customer Lifetime Value (CLV)" is increasingly acknowledged as a crucial metric in customer relationship management (CRM) for acquiring, cultivating, and retaining the most valuable customers. There are main organizations that failed to use CLV metrics properly. The organizations first have direct interaction with clients who are not desired to take services or face complexities in customizing the level of customer interaction for value optimization (Thompson, 2001). Furthermore, Rosset et al. (2003) explored that the issues involved in customer interaction can be eliminated via using segment-based strategy. The organizations can shift their emphasis to projection of the overall contribution of all the segmentation and findings the most attractive segment rough exclusively defining the lifetime value on the basis of the results of the existing campaigns and not considering the other factors such as customer loyalty and referral groups.

Venkatesan and Kumar (2004) further evaluated CLV framework's efficacy as a basic construct for selection of the prospective clients and effectively allocating the marketing resources. The implication of CLV in impacted through using the marketing interaction processes accomplished through using of different communication channels. Based on their results, it is interpreted that client selection done on the basis of CLV framework proves supportive to gain increased earning with the time rather than using other criteria of customer selection. In similar context, Kumar et al. (2010) affirmed that transactional behavior of the consumers is not sufficient criteria for consumer assessment purpose, however, customer interaction is the main criteria for governing adequate customer evaluation process. Furthermore, Thomas et al. (2004) affirmed that for enhancing business profitability, optimization of customer interaction techniques is the major requisite. Not using these optimum techniques in the marketing expenditures for the purpose of attracting the clients and retaining them affects the profit ratio negatively. This highlights the vulnerability of profitability to variations in meticulously designed marketing spending tactics intended to optimize client acquisition and retention. Kumar (2024) illustrates the utilization of Customer Lifetime Value (CLV) in identifying customers with higher profit potential, optimizing the management and incentivization of current customers according to their profitability, and prioritizing investments in high-profit customers to reduce attrition and ensure future profitability. The author promotes customer-centric strategies for the allocation of marketing resources to enhance effectiveness, synchronize product offerings with customer requirements and timing, anticipate customer attrition for prompt intervention, manage multi-channel shopping behaviors, and evaluate the worth of customer referrals.

Kumar (2008) defines Customer Lifetime Value (CLV) as "the total financial contribution from the current period into the future," thereby indicating the future profitability of the firm. Venkatesan and Kumar (2004) define the Customer Lifetime Value (CLV) metric as the present value of future profits derived from a customer throughout their lifetime relationship with the company. The metric assesses the value of each customer to the company and facilitates tailored treatment based on their specific contributions, rather than employing uniform strategies for all customers. Furthermore, the total of all customers' lifetime values forms Customer Equity (CE). CLV is a comprehensive metric of individual customer profitability, while CE acts as a collective measure. Upon calculating the Customer Lifetime Value (CLV) for its clientele, a company can devise strategies by optimizing resource distribution, predicting future customer expenditures, and balancing the acquisition of new customers with the retention of existing ones, with the objective of maximizing overall returns. Kumar and Reinartz (2016) assert that customer value is a bifurcated concept. To achieve success, firms must generate perceived value for customers. Marketers are responsible for assessing customer perceived value and conveying it through different components of the marketing mix. Secondly, customers contribute value through various forms of engagement, encompassing Customer Lifetime Value (CLV) in its most comprehensive sense for the organization. Therefore, marketers must assess and strategically oversee customer value across the organization, including it into real-time marketing choices.

For the purpose of customer value assessment, CLV metrics has an extensive adoption rate in the healthcare sector. For the assessment of CLV for particular patients through emphasizing on the difference between patient and customer loyalty, Hosseini and Mohammadzadeh (2016) suggested the use of Recency, Frequency, Monetary Value (RFM) model. The authors emphasized that in hospitals maintaining customer relationship is a vital phenomenon. They suggested that identification of the multiple categories of patients can be done using a categorization model and with the help of this marketing tactics can be developed accordingly. In similar context, Tarokh and Esmaeili Gookeh (2019) emphasized on the use of Markov chain and data mining as a combined approach for modelling CLV with high accuracy for examining the actual patient value. Their research results were based on patient behavior and are supportive for forecasting the future treatment process required for particular patients and using suitable patient management tactics. Another research conducted by Scriney et al. (2020) was focused to project rate of customer attrition with insurance data for dealing with the complexities faced in CLV estimation due to not having required history of patient data. The authors suggested a new method for generating the unknown parameters for calculating CLV with the use of the particular data warehouse architecture in amalgamation of a versatile prediction and validation methodology. The results showed that with the help of data gap alleviation, the firms can have enhanced and accurate calculations of CLV measurement, and this proves to make the marketing and sales tactics optimization. Furthermore, another literature study by Donkers, Verhoef, and De Jong (2007) for estimation of the CLV in the insurance industry, assessed different models and their predictive capabilities. The authors conducted a comparative study by comparing simple aggregated models used for customer relationship with complicated models that are centered on individual services such as cross-buying and retention dynamics. In their study authors conducted 4 years computation of CLV separately for every customer. Gaining insight into study results revealed that for estimation of CLV, simple models have more effective use, and these models signify the customer retention role for devising the CLV estimation models with high accuracy. In similar manner, Pfeifer (2011) further explored methods for assessment of the current-customer equity through accessing the summary data reported by companies with particular emphasis on the calculation of sum of CLV for determining the current level of customer relationship.

The study also investigates the differences between monthly, quarterly, and annual models for CLV, emphasizing that these models are not interchangeable despite equivalent retention and discount rates. The findings indicate that traditional retention rate and revenue estimates derived from average customer numbers tend to underestimate values when acquisition rates are low and conversely, they tend to overestimate values when acquisition rates are high.

Fader and Hardie (2010) introduce a relationship duration model aimed at predicting retention rates beyond observed data. Their study demonstrates that overlooking these dynamics leads to an underestimation of the residual value of the customer base compared to aggregate analyses that fail to include such factors. Additionally, they investigate the consequences of ignoring retention dynamics in calculating retention elasticities and their findings reveal that commonly reported values tend to underestimate the actual impact of improvements in underlying retention rates.

However, most CLV models focus solely on individual customer behavior. While some research (Bruni & Sugden, 2008) (Kessler et al., 2005), have touched on family-driven purchasing behavior, its application to insurance is underexplored. This study seeks to fill this gap by investigating how claim experiences impact the likelihood of dependent family members adopting new policies. Table 1 looks at studies done on CLV

Table 1: Previous studies related to CLV.

Studies	Type of Data	Industry	Key Findings
Fenny, Kusi, Arhinful and Asante (2016)	Survey – Interview	Health insurance	The low rate of health policy renewal is influenced by sociocultural and system-wide factors, such as cultural norms, insufficient social infrastructure, and inadequate care quality.
Ahire and Rishipathak (2018)	Survey - Questionnaire	Health insurance	Younger age, higher income, and high healthcare costs have emerged as significant indicators of policy renewal.
Kautish, Khare and Sharma (2022)	Survey - Questionnaire	Health insurance	A company's high performance and strong reputation are crucial for customer retention. Customers with high inertia are more likely to stay with their existing insurance provider.
Bagchi, Agrawal, Kavita, Sunita, and Thomas (2024)	Survey- Questionnaire	Health insurance	Renewing or purchasing health insurance is independent of one's professional occupation or level of education. Instead, the renewal rate is largely influenced by past satisfaction with the insurance provider.
Smith, K. A., Willis, R. J., & Brooks, M. (2000)	Case study	Health insurance	how insurance companies can increase customer loyalty and also streamline claims processing. Intention is to increase overall profitability and explore better premium pricing methods .

Kautish, P., Khare, A., & Sharma, R. (2021)	Survey-Questionnaire	Health insurance	How reputation, service performance, and emotional responses affect customer inertia in health insurance policy renewals. These factors significantly influence customer's reluctance to switch providers and their tendency to renew policies
The current Study	Experimental	Health Insurance	The incidence of insurance claims positively affects renewal retention; An increase in PHC-related claims led to a surge in retention rates; The policies with claims are associated with higher conversion rates for dependent family members.

Building on the prominent studies of Customer Lifetime Value (CLV), we introduce a novel concept termed 'Family CLV (henceforth referred to as Customer Family Value or CFV), which extends CLV to include family members of insurance policyholders. We analyze how filing a claim impacts the propensity of advocating for a new insurance policy among dependent family members, thereby exploring the concept of 'Value Creation' from the family tree. The following section outlines these research gaps and highlights the contributions of this study.

2.4 Research Gaps and Study Contribution

Notwithstanding the expanding literature on insurance renewal behaviors, a significant limitation remains in the methodological approaches utilized in current research. The predominant dependence on survey-based and observational studies, although useful for gathering self-reported attitudes, intentions, and past behaviors, is inherently plagued by response biases, social desirability effects, and constraints in establishing causal inferences. In the absence of rigorous controlled experimental research designs, it is difficult to separate the effects of behavioral interventions from confounding variables, limiting the capacity to obtain robust, generalizable insights into policyholder decision-making processes.

Identification of the key gap in methodology showed that there is an urgent needed some experimental studies for manipulation of the research variables in an orderly manner for examining the impact of those variables on the client decisions of renewal of insurance. In the field of consumer decision making, nudge theory and regulatory focus theory are used as widely used behavioral theories, however in the health insurance sector, the implication of these theories is not considerable yet. Past researches explored these theories, however separately and thereby for the purpose of long-term customer retention, the critical interaction of nudging techniques and regulatory regimes and cognitive biases is found to be limited. This kind of theoretical implication in fragmented manner restricts to apply behavioral models in a comprehensive manner for the purpose of prediction of the purchase decision making behavior of policy holders. The existing research studies are affected with noteworthy limitations of not exploring the family-oriented CLV metrics in customer retention in the health insurance sector. Comparatively the conventional CLV models keenly emphasize on policyholders' financial contribution irrespective to the considerable impact exerted by the policy holders on the insurance holding decision of the family members.

In general, family members are independent to take their decisions for their health insurance, however within the policy of the primary policyholder, the coverage of the dependents is linked. The ignorance of the dynamic results causes not having complete assessment of customer value. In the past literature, there is no specification about a key weakness of the structured metrics in terms of quantifying policy holder retention's cascading effect on the insurance behavior of their dependents. There is no specification in the current studies about CFV and its strategic implications as a new paradigm which has implications over traditional CLV models with the accumulation of policy holders' and their dependents' combined lifetime value.

In determining the overall profitability of a firm, misunderstanding the CFV affirms that insurers do not have exact estimation of the actual economic benefits of using customer retention strategies influencing key trends of family-based decision-making in the health insurance sector. The selected study will intend to fill the gap found in past studies via conducting experimental research in a rigorous manner for evaluating behavioral drivers of customer retention in the insurance sector in a controlled manner. The presented research involves application of Regulatory Focus Theory (RFT) and Nudge Theory in the form of a unified logical framework for having in-depth understanding of interaction between the regulatory orientation and behavioral interventions for shaping policy renewal decisions of policy holders. This study also discussed about a new metric named CFV in the form of an empirical grounded approach for measuring the financial impact of policy renewal and insurance decisions of the dependents on the profitability level of the firms. By doing so, this research not only addresses the methodological, theoretical, and practical limitations of prior studies but also establishes a comprehensive foundation for enhancing long-term customer value strategies in the insurance sector. In the discussion below, the key issues faced in the process of consumer decision-making and retention are discussed:

2.5 Puzzle fixing:

Mr. and Mrs. Sharma sat at their dining table on a chilly winter night as the comforting aroma of freshly brewed chai filled their home, engrossed in a choice that epitomized middle-class prudence: the choice to fortify their financial security through health insurance. Although the couple had been lucky so far, they were aware that additional unknowns lingered in the background and that medical issues may cause their financial stability to collapse. They recognized that the unsustainable rise in healthcare costs needs a planned financial safety net.

An insurance from a reputable insurer for entire family including two kids was chosen after they conducted thorough research, compared policies carefully, and sought advice from people they trusted. Mr. Sharma told his wife, "It's just a precaution," as he signed the papers. "Maybe it will never be needed." At first, they didn't do much more than pay the premiums; it was more of a chore than an investment, a normal outlay that they continued to do without giving it much thought, like paying the bills on a regular basis or the instalments on a mortgage. The renewal notifications came at regular intervals, and they kept paying the premiums without giving it much thought, seeing the policy more as a passive financial mechanism than a physical layer of security. But in an unexpected and upsetting way, their policy's actual intent will soon be put to the test.

Unfortunately, one day Mrs. Sharma's minor exhaustion turned into constant shortness of breath, making even the most basic chores more challenging. They went to the doctor because they were worried, and the results showed that there was a major problem that needed fixing right now. They were able to calm their nerves a little since they knew they had insurance, something they had worked hard to get. "This is precisely why we have a policy," Mr. Sharma assured his wife, his unshakeable trust in the system meant to protect them when they were vulnerable. But when they got the letter rejecting their claim, their optimism was crushed. Their claim was refused by the insurer on reasons that seemed to be intentionally evasive, capricious, and based on technicalities found in the complex legalese of the policy's small print. Their objections were escalated via many phone calls, appeals, and emails, but the insurance remained adamant in their rejection. They contested the decision. "After four years of paying premiums, they still won't cover us when we really need them?" A combination of annoyance and disbelief made Mrs. Sharma's voice tremble.

Their trust in the organization that was supposed to safeguard them had been dwindling, and their view of insurance had transformed from a foundation of financial stability to a bureaucratic mechanism designed to avoid accountability. As their interactions concerning insurance progressed, their disenchantment became more apparent, and their chats became more hostile. Logic told them to cut ties with this insurance and look into other options. Even though they were confused by what they did when the renewal notification came a few months later; they renewed! Conventional reasoning was disproved by the judgment. When they needed their insurance the most, why stick with a company that flat-out let them down?

For dealing with the key hurdles of cognitive and logistical nature, Mr. Sharma wants to show that they decisions were reasonable. For him, the main considerable issue was not having any health insurance policy. Despite the compliant with the insurance service provider, the more considerable issue was not having health insurance. Holding the new policy was a prospect for Mrs. Sharma considering here past medical history. The new policy development requires her new medical assessment, detailed paperwork and even there is threat of rejection of insurance policy. Despite the shortcomings of their current approach, they felt secure in their familiarity with it, and the idea of learning a new method was intimidating and unclear. The psychological toll of transition was another factor. Furthermore, despite their frustration, their insurance continued to provide some additional benefits, such as wellness initiatives and preventative health examinations. Although they had incorporated these into their daily healthcare regimen, the financial benefits were minimal. These excuses belied a more fundamental cause: chronic immobility. For four years, the premium deduction had been a mindless, automated procedure. Terminating it appeared to be disruptive and maybe hazardous, akin to tempting fate. The psychological effects of status quo bias the innate human propensity to prefer the status quo over change—were mostly to blame for their delay.

During a family reunion, the cousins of Mr. Verma brought up the plan for health insurance after the inspection. He had some trusted and known people whose advice he considers valuable, so he asked them about the insurance policy they have. Mr. Sharma spoke with hesitation. He was in a dilemma whether it is a right act to clearly mention that he is not satisfied with his existing insurer because the insurer does not even resolve the complaints and rather persists him for policy renewal. There policy was for four years. He was in the mid-state of realism and frustration. Despite having shortcomings in the existing insurer's policy, he preferred that it is good to have their policy rather than being uninsured. Not being explicitly mentioned this thing, their words clearly specifying that their insurance choice though having flaws was even a viable option. In the period of a week, Mr. Verma purchase insurance policy forms the same insurance company. In the following month, there was seen a ripple effect in his entire circle. The suit was followed by his neighbor, and aunt and brother-in-law of Mr. Sharma. They were influenced more by normalization and perceived social proof than by thorough market research or direct advertising. Despite their dissatisfaction, Sharma's adherence to their policy conveyed a message of acceptance. A key idea in behavioral economics is Customer Family Value (CFV), which explains how keeping one policyholder has an indirect impact on the financial choices of their immediate and extended network. They had unwittingly turned into passive influences.

This was a strong phenomenon, however, form the insurers' point of view it was not appreciated much for the purpose of having a growing client base in the long run. Insurance industry from historical trends has high reliance on CLV metrics for measuring the long-term worth of individuals on the basis of history of claims, premiums and retention rate. CLV framework works in isolation, which only considers policy holder's financial impact without giving any consideration to its prolonged impact on the family members. As per the assumption of CFV model, insurers can increase their long-term income through retention of individual policy holders because with this pattern they can have a vast network of individual policyholders. Insurance retention is not the case where all individuals have their own decision always, as found in the case of Mr. Sharma. However, insurance is a practice of psychology, personal behavior and social dynamics. Their constant renewal was not a testament to the excellence of their insurer, but rather a manifestation of cognitive biases, perceived switching barriers, and intergenerational influence.

The insurers consider that a network driven strategy which utilizes habitual participation, social influence and intergenerational policy adoption can be used as an auxiliary for the individual-centric model for the quest of retaining the clients. The story of Sharma family signifies the economic and behavioral facts about insurance policy in a wider context. Insurance loyalty is not because of having service excellency; however, it is the result of peer pressure, threat of risk taking and personal contentment.

Insurance loyalty is more frequently the consequence of complacency, risk aversion, and peer pressure than it is of exceptional service. Their decision to renew was influenced by habit, convenience, and cognitive aversion to change rather than by satisfaction. This has a big impact on the insurance industry. In addition to claims management and pricing measures, insurers can employ behavioral reinforcement techniques including automated renewals, seamless digital engagement, and proactive wellness-driven incentives to improve long-term retention.

Insurers would be able to deliberately use family-based marketing strategies by recognizing CFV as a key business indicator and providing bundled plans, multi-member discounts, and referral incentives that capitalize on existing trust networks. The Sharma's had no intention of influencing the insurance sector.

Yet, their personal, habitual decision, one renewal at a time, was part of a larger, systemic force shaping consumer behavior. Their story is emblematic of millions of policyholders worldwide who, despite dissatisfaction, continue renewing due to habitual inertia, perceived effort barriers, and the silent but profound power of social influence. For insurers, the question is no longer just "Why do customers leave?" but rather, "Why do they stay?" The answer lies not merely in claims processing, but in understanding the behavioral science of decision inertia, embedding insurers into daily financial habits, and unlocking the exponential value of intergenerational customer networks.

This idea is best illustrated in the following Figure-1- how insurers strategically approach customer retention.

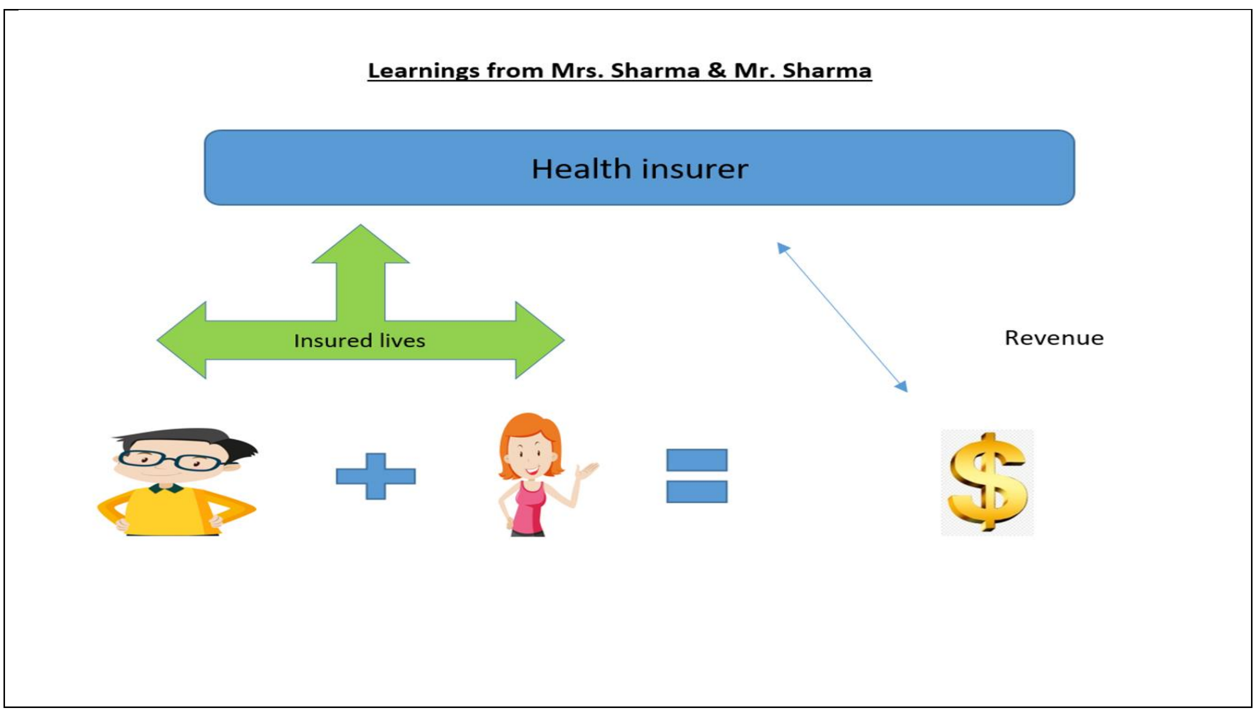

Figure 1: how insurers strategically see customer retention.

The financial stability of insurance companies is dependent on the aggregate of insured persons, who are the industry's primary source of income and a buffer against risk. The solvency and profitability of the insurer are guaranteed by a pooled risk structure in which each policyholder contributes to it. Premium payments from a diverse customer base finance claim payout.

Yes, it is a business issue. Claim instance is the starting point stating that renewal retention is higher for such customers . It may not always be true that policy holder's churn out on nonpayment of claim or retain better with acceptance of a claim. The competitor health insurance companies may not like to have a customer where there was a claim earlier; especially when it was rejected. Also, the number of members may be more than single individual hence churn becomes difficult, especially where there is pre-existing condition. We have tested renewal retention against instance of claim and that retention is better than those without any claim.

The economic principle of risk pooling is central to this model, which means that a larger number of insured lives means fewer expensive claims and more stable income streams. In this model, families stand out as valuable clientele since their combined policy purchases help the insurer build a stronger risk portfolio and ensure the company's longevity. Such homes function as nodes within larger social networks, enabling multi-generational policy extension and interdependent financial decision-making; hence, retaining families like the Sharma's is not just a transactional connection but a strategic retention strategy.

By taking into consideration the interconnectedness of policyholder behavior, how one insured person affects the financial decisions of their immediate and extended family members, the Customer Family Value (CFV) paradigm goes beyond conventional Customer Lifetime Value (CLV) models.

From a behavioral economics point of view, insurance companies take use of what is known as the "family tree effect," in which a single satisfied client increases the likelihood that their friends, relatives, and acquaintances would also purchase insurance. This effect stems from the well-established idea of social proof and herd behavior, according to De Bondt & Thaler (1985). People tend to follow the financial decisions of their trusted peers, especially when it comes to areas like health insurance that are filled with long-term commitments and uncertainty.

Studies conducted about the financial behavior of consumers showed that the choice of insurance of individuals is the result of social reinforcement. Prior to choose any insurance service provider, the policy holders tend to take consultation with family members and friends rather than taking any isolated decision. The behavioral intention proves an advantageous aspect for the insurers for improvement in the rate of retention and minimizing the customer acquisition cost. CFV proved a self-sustained mechanisms for increasing the penetration rate of insurance policy by not even putting any promotional tactics which demanded for huge capital investment. CFV had several associated advantages of growth of the rate of client acquisition through reinforced policy decisions driven through network and minimum marginal cost and constant rate of market penetration.

In the insurance industry, companies seek to generate income from selling of policies and retaining customers in the long term rather than meeting the claims. Regardless of the frequency of claims, empirical industry data indicates that policyholders who renew their coverage on a regular basis provide a more stable and predictable income stream than high-turnover clients whose policies expire due to dissatisfaction or competitive switching.

The insurance companies effectively use behavioral retention method for inspiring the clients to have policy renewal consistently. For meeting this goal, the insurance companies offer incentives to the clients which are non-claim based, new wellness programs and preventative healthcare checks. With the help of this method companies meet dual purposes. Firstly, they tend to give value added services to the customer to make them feel that they are getting additional benefits in the policy despite availing any medical services. This makes the clients realize the perceived utility of the policy, not just the claim advantage during medical emergencies. Secondly, insurers trigger the biases considering that people generally tend to maintain their financial arrangement in present rather than facing the complexities involved in the switching to other insurers. For increasing the engagement level of policy holders, the insurers can provide them regular health and wellness benefits and by doing this, they increase the retention rate of policy holders and increase rate of policy renewal.

The insurance companies seek to find policy holders like Mr. Sharma as only an income source, however, using them as a portal of insurance network for policy retention in different generations and in their social connections. The retention models used by insurers which are CLV centric work as strategies for client acquisition and engagement. Under these strategies, a key emphasis must be given on the developing habits of getting insured by people and continuation of policy for next generations. With the use or CFV metric, the insurance companies can enhance their ability to have projection of the revenues for future. This will ensure that their customers are seen as compounding assets rather than just a series of transactions. Insurers can achieve exponential growth through interdependent customer ecosystems and maximize retention longevity by integrating their services into customers' financial lives through initiative-taking engagement, automated renewals, and wellness-driven policy reinforcement.

"How do we transform policyholders into long-term influencers within their familial and social networks?" has supplanted "How do we retain individual customers?" as the primary concern for insurance providers in today's dynamic and competitive market. Sustainable, intergenerational insurance uptake and financial stability may be achieved via the strategic integration of behavioral insights, risk-pooling economics, and network-based retention mechanisms. The theoretical underpinnings and testable assumptions that form the basis of this study's empirical examination are laid forth in the section that follows.

2.6 Conceptual Framework and Hypotheses

From the health insurance company's perspective, the cost of acquisition is higher in the first year due to significant incentives offered to new customers; Subsequent annual renewal commissions and additional incentives follow. The first four years are typically the most profitable because the claims are lower, due to stricter policy terms, and most of the underlying immediate coverage would have been utilized by then. This can provide opportunities for agents who can lead the insurers towards other policy providers, in aspiration of better incentives. Thus, devising effective retention strategies is crucial for the company for several reasons. First, losing a profitable cohort diminishes overall profitability and shareholder value. Second, the initial acquisition costs are high, making it expensive to replace lost customers. Third, retention losses are difficult to compensate for with new sales alone. Finally, maintaining a connection with customers is essential, as losing this connection can negatively impact long-term business relationships.

Figure 2. presents the company’s implementation strategy based on the 2x2 decision matrix, which evaluates risk propensity and Customer Lifetime Value (CLV), targets different customer cohorts to optimize retention efforts.

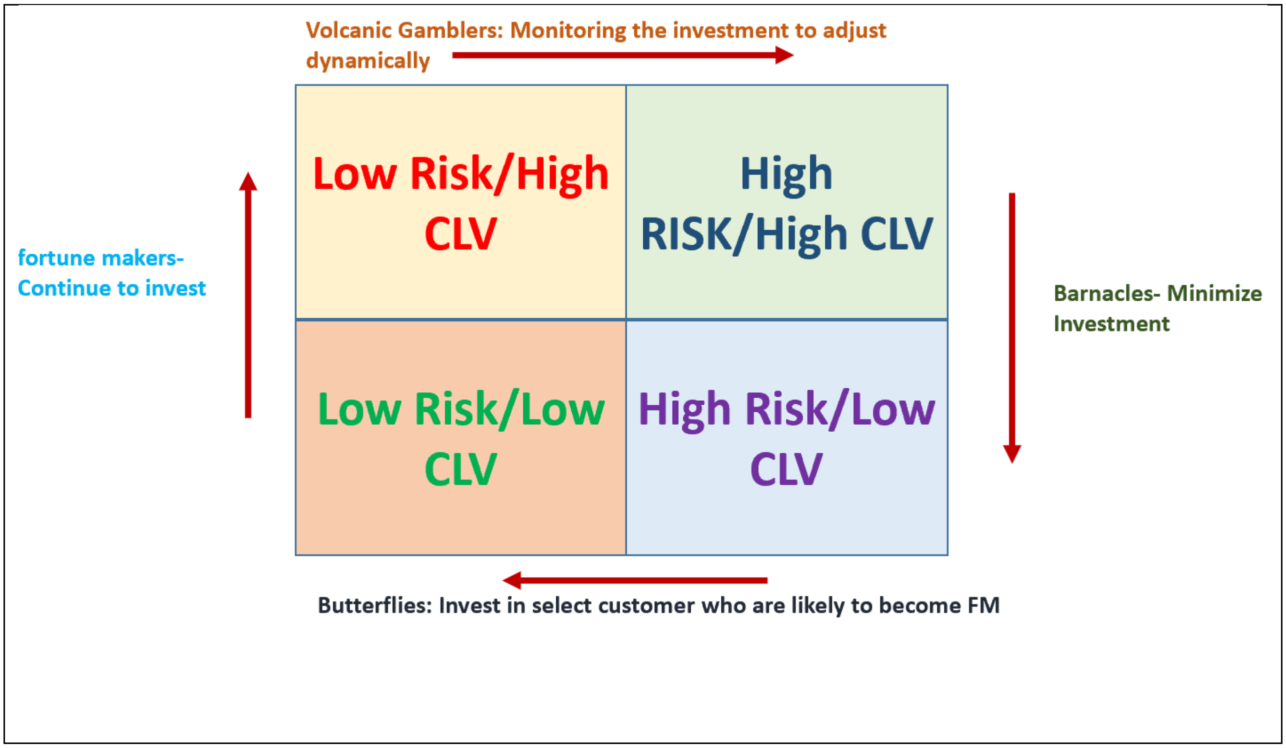

Figure 2 Implementation strategy based on Risk Propensity and CLV

For high-risk, high-CLV customers, referred to as "Volcanic Gamblers". These are high-net-worth individuals with significant premiums and sum insured. They may be prone to switching due to dissatisfaction with minor claims or limitations on enhancing their coverage. Careful management and minimal intrusive follow-ups are essential to retain these clients without alienating them. High-premium policyholders constitute a disproportionately valuable segment within the insurance market, contributing significantly to an insurer’s revenue base while simultaneously exhibiting high volatility in retention behavior. Unlike mid-tier policyholders, whose renewal decisions are governed by habitual inertia and switching costs, high-net-worth clients possess greater financial flexibility, heightened service expectations, and a reduced tolerance for inefficiencies in claim processing and policy management.

The decision-making framework of this segment is best understood through prospect theory, status quo bias, and service-dominant logic, which collectively suggest that individuals with substantial financial investment in a service attach heightened sensitivity to disruptions, particularly in industries where trust, responsiveness, and exclusivity are paramount.

Research conducted related to customer experience management affirms that rich customers, whether high-stakes speculators or luxury buyers, base their allegiance on the idea of preferential access, dependability, and superior service standards rather than cost effectiveness. Retention strategies of insurance companies have several benefits including efficient process of claims, and price incentives. However, the companies fail to resonate other segments whose preferences are having elite service facilities and seamless experience and assurance of full responsiveness. In addition to contributing a disproportionately greater lifetime value (CLV) than regular customers, high-net-worth policyholders are also the most vulnerable to quick policy cancellation, which is frequently brought on by small service inefficiencies.

A case in point is the executive policyholder who maintains a premium-tier insurance plan valued at tens of thousands of dollars yet is prompted to consider switching insurers due to a delay in processing an insignificant claim (e.g., a $1,000 hospital bill). While the financial impact of such an event is negligible relative to their wealth, the psychological perception of inconvenience, lack of prioritization, and suboptimal service engagement serves as a catalyst for disengagement. This aligns with expectation-disconfirmation theory, which posits that customers experiencing a discrepancy between anticipated and actual service quality are more likely to engage in negative attribution biases and switching behavior. Unlike standard policyholders, who may endure inefficiencies due to search costs and perceived effort barriers associated with switching, high-value customers possess both the means and the inclination to engage in competitive shopping behaviors, leveraging their financial status to negotiate favorable terms with rival providers.

This tendency signifies the recalibration of conventional models of client retention and replaces the reactive claims management with proactive approach and use of the experience-driven relationship framework. Insurers must use a multi-tiered, concierge-style retention model that incorporates behavioral engagement reinforcement mechanisms, exclusivity-driven privileges, and personalized relationship management in order to reduce churn risks and maintain engagement.

First, the implementation of dedicated, high-touch client management systems is essential, ensuring that high-value customers are assigned relationship managers or executive-tier service agents who provide concierge-level assistance and proactive service resolution.

With the provision of humanized services and prioritized customer engagement results into dealing with customer dissatisfaction issues through providing increased services via using responsive and personalized services. For example, when any premium policy holder face the issue of having claim process delayed, the immediate relationship manager of the insurance company must have intervention in this case and must process in such a way that policy holder can have update of the claim clearance status in real-time manner and expedition of the approval through engaging with the claim-processing department in a direct manner for minimization of the client frustration level and reinforcement of the prioritized services to the clients as perceived by them. In this relation perceived control theory affirms that when the customers receive services in a transparent manner their trust on the insurance company builds stronger and it results into reduction of chances of switching to other companies.

By the provision of exclusive retention incentives, the insurance companies can reinforce differentiating the premium policies in a tangible and experiential manner. Dissimilar to policy holders who are price sensitive, the client with high-net-worth derives increased value not in terms of discounts but as access-based privileges. Therefore, in the policy structure, there must be constitutes some exclusive benefits for the policy holders such as fast track approval of claims, top-tier healthcare providers, premium hospital accommodation, and extension of the health policy coverage at international level. The status signaling theory covers all these privileges. This determines that prosperous and premium policy holders do not tend to find any monetary differentiators rather than they seek to have good service experience unlike to other policy holders. Therefore, the premium segment clients show high loyalty when they receive services according to their social status via accessing the health benefits that are prestige driven and this kind of service retains them in sustained manner.

It is also imperative on the part of insurers to have communication strategy recalibration for policy alignment with the premium policy holders' preferences who do not have any tolerance for extreme promotional engagement. Unlike general policyholders, who may respond positively to high-frequency engagement campaigns, affluent clientele prefers concise, highly relevant, and solution-oriented communication touchpoints.

With the research conducted it is affirmed that premium consumer engagement underlines that due to excessive interaction the perceived exclusivity is diminished because it leads to commoditization of perceived services and consumer disengagement. Insurance companies can enhance their service provisions via inclusion of AI driven predictive analytics for multiple purposes including exclusive invitations for upgrades, tailored micro-targeted policy updates and enhancement of the service process in accordance to the customer preferences and their consumption patterns. For instance, with the provision of AI-driven personalize messages related to the history of claims, premium policy trends and preferred information to the customers will make the communication process relevant, concise and valued augmented. With the retention of the premium policy holders, the financial benefits balance the cost incur in the service process.

With the research results based on the customer equity modelling, it is affirmed that high-premium policy holder can have a lifetime value around 5 to 10 times greater than any other standard policy holder makes retention cost-per-dollar return in an exponential manner in a more favorable manner for exclusive customers. The affluent client not only support in revenue contribution for the insurance companies, but they also work as influencers in both social and professional context and do amplification of the CFV through policy expansion in organic manner via giving referrals in a trustworthy manner.

As a result, actively improving retention strategies for this market segment boost competitive standing in the high-net-worth market while also stabilizing revenue streams. Even though they might be very profitable, high-value policyholders pose special retention issues that call for a shift away from conventional, claims-focused engagement strategies. A paradigm shift in insurer strategy from transactional service administration to proactive, experience-driven customer engagement is required due to their reduced switching barriers, elevated service expectations, and financial agility. Insurers can reduce attrition risks and increase the perceived value of continuing policy retention by implementing precision-based communication, exclusivity-driven benefits, and dedicated relationship management to strengthen long-term policyholder loyalty.

The affluence clients only seek for seamless services which are reliable in nature rather than having cost-based differentiation. Therefore, the insurance industry needs to have transition of the services from price-competitive strategies customer-relationship-centric strategies where personalized, responsiveness, optimized and wellness integrated services are provided to the clients. The insurance companies that embed themselves as trusted, indispensable service partners rather than generic risk managers will achieve sustainable, high-value retention, driving long-term profitability and market differentiation within the premium insurance segment.

Contrary to this, customer with high risk and low CLV are the policy holders for long-term with some pre-existing conditions that do not have tendency of switching to other policy companies as they have tailored insurance coverage preferences. Other than this, the customers having high-risk and low mobility who are mainly elderly people having chronic illness face the actuarial challenges tend to have a change by the insurance companies to switch from traditional customer retention framework to actuarial sound cost-containment model.

Due to adverse selection barriers—competitive insurers frequently impose medical underwriting restrictions, exclusion clauses, or unreasonably high premiums for pre-existing conditions—this segment is structurally retained, in contrast to discretionary policyholders who participate in competitive shopping behaviors.

The affluent policy holders show near-zero voluntary churn and have loyalty programs as traditional consumer engagement strategies. However, the medical loss ratio to a high level when the claim amount received by the policyholder is more than the premium paid by him or her, it causes risk to financial sustainability of the insurer and for dealing with this issue, there is experienced a strategic intervention for maintaining fiscal balance to meet the service provision but no compromise with the regulatory aspects. This can be exampled with retired educators aging 60s and hold a policy for more than 15 years seeking for expensive treatment frequently for different severe health issues including cardiac rehabilitation and dialysis. They remain highly reliant on the insurers and make frequent claims for health emergencies. For addressing the actuarial imbalance, a tripartite strategy can be workable for the insurance companies which incorporate computerized processing of claims, lean services of administrative aspects and policy adjustment in structured manner for alleviating increased claims for assuring care accessibility in essential and emergency cases. This automation process is highly imperative for policyholders who are high utilization of customers because there is a necessity for having frequent reimbursement of the persistent medical expenses for particular service provisions including consultation by specialists, insulin therapy and managing chronic diseases.

Research studies conducted in the field of operational analytics of healthcare services recommend that in the process of claim adjudication, automation process can minimize the administrative cost of each claim by around 40% and hence minimize financial burden for insures during maintaining service continuity.

Insurers can effectively separate legitimate, compliance-based claims from excessive or duplicate submissions by utilizing machine learning-driven anomaly detection algorithms. This allows them to maximize cost efficiency without interfering with the policyholder experience. Second, because loyalty-driven retention investments result in diminishing marginal returns for fundamentally captive clients, insurers must deprioritize non-essential engagement expenditures from the standpoint of customer servicing. Chronically ill clients need consistency in claims processing instead of individualized interaction, in contrast to high-net-worth policyholders who expect unique benefits and high-touch relationship management.

Gaining insight into research conducted in relation to consumer behavior in the insurance sector revealed that making promotional investments in a sustained manner is not supportive to enhance client retention in the same proportion in the specified segment and it becomes financially judicious for insurance companies to allocate the organizational resources for maintaining efficient processing instead of taking customer engagement initiatives in discretionary manner.

In a lean servicing model, there is limited interaction of the policyholders to indispensable functions such as modifications of claims, reminder updates for policy renewal and updates for regulatory compliance and ensuring policy holder retention in cost-effective manner and alleviating redundant administrative overheads. The insurance companies must also do recalibration of the policy terms for alignment of the cost-sharing mechanism for claims acquaintance and using actuarial risk balancing measures including incremental co-payments, deductible adjustments for elective procedures, and structured reimbursement caps for non-critical treatments.

The regulator directives restrict insurance companies from repudiating insurance coverage to long-term policy holders in arbitrarily manner for claiming for chronic conditions, however modifications in the policies in data-driven manner improvise the financial sustainability without any compromise with the veracity of the coverage. For example, on the basis of cumulative claim history, the introduction of the staggered co-payment tiers helps to ensure that high-MLR policyholders make proportionate contribution to their consumption patterns of healthcare and reduce the unnecessary financial burden on the risk pool of the insurers.

Insurers can also negotiate value-based care contracts with healthcare providers, moving away from fee-for-service reimbursement models and towards performance-based care structures that put long-term patient health outcomes first. This approach has been shown to lower chronic-care costs by as much as 20% over a number of years. The sustainability of high-risk policyholders must be incorporated into a thorough risk-pooling and reinsurance plan from a macroeconomic standpoint so that their continuous presence in the insured portfolio does not jeopardize underwriting profitability.

The premiums gained from the young policy holders work as a subsidy mechanism in the overall risk pool of the insurance companies, however, the old age policy holders and those who are chronically ill have an increased ratio of claims and it demands the insurance companies to force risk-adjustment transfer, reinsurance provisions, risk corridors for chronic diseases for giving claim exposures to the increased number of applicants. Under the risk equalization frameworks, regulatory negotiations advocate for offsetting the increased financial load for dealing with high-risk population in disproportionate way by the provision of government subsidies and agreement of public-private sharing. With these provisions dual benefits are gained such as the solvency of the insurers and giving increased healthcare coverage access to equitable level. Managing high-risk adequately and policy holders with low-mobility demands for transition from traditionally adopted retention-driven customer relationship model to actuarial framework which is sustainability-focused under which different priorities are set including restructuring the strategic policy, risk management via predictive analytics and cost-effective claim processing.

A risk-balancing approach in a structural manner is required for meeting multiple purposes including technology automation, efficient operational functioning, and actuarial recalibrations which are supportive to ensure viability of the policy in the long-term. Claim adjudication in an automatic manner value-based reimbursement, minimizing unwanted expenditure on client engagement and adoption of risk mitigation mechanism driven through regulatory regimes prove supportive measures for the insurance companies to serve the high-cost policy holders consistently without any issue of financial sustainability. In the contemporary evolved landscape of health insurance where diverse groups are involved including young policy holders, aged population and chronic diseases affected people, it is challenging for insurance companies to ensure retention of the high-risk policyholders as well as sustaining them in the portfolio in long-run irrespective to any compromise with the aspects of stability and solvency.

There is a high probability of switching of the short-term policy holders who have low-risk propensity and low CLV therefore they are termed as butterflies. Retention of this group of policy holders is vital for insurers because they hold significant potential to become higher CLV policy holders. A strategically significant segment is policy holders who are low-cost but high-future value, but they are under-leveraged and they need for having a longitudinal engagement framework which focuses on retention policies, expanding policy value in an incremental way and behavioral reinforcement for optimization of lifetime customer value. This segment involves professionals in the early stage of their career and do not have much utilization of the healthcare coverage and have minimal propensity of claims, generate minimum considerable revenue but also pose underwriting risks in insignificant manner and thereby they are financial neutral. However, with the transition of their lifecycle stages after being married, parenthood, homeownership, and career advancement, their potential to evolve into high-value, multi-product customers increases exponentially, positioning them as essential long-term assets in an insurer's risk portfolio.

This is explored via doing detailed research in the field of customer lifecycle analytics and behavioral economics holding insurance policy at an early age have significant impact on the policy retention in the long-term as they develop, and they have low probability to switch to the other providers having a good initial bond with a particular insurance company irrespective of having incentives which are competitor driven.

Therefore, reducing early attrition risks is not the only challenge; it is also crucial to promote a policyholder maturation trajectory, in which entry-level policyholders become high-contribution, multi-policy consumers through targeted benefit expansions, structured engagement, and incentives that encourage habit formation. As an illustration, take the case of a 27-year-old professional who just started working and chose a minimal health insurance plan, mainly out of compliance rather than personal need.

In the early stage of life, the policy holders to not have much utility of insurance policy and therefore they are overly concerned with price and have low affinity to any particular brand, and they are seen as susceptible by the rivalry firms and their competitive strategies of acquisition. Therefore, the insurers offer them sundry benefits including vision coverage and dental coverage at comparative price point. Responding this adequately needs the insurance companies to adopt a policy holder engagement strategy which is multi-tiered integrating personal consultancy, proactive coverage evolution and behavioral retention to ensure commitment of the policy holders in the long run.

For establishing a good alignment of the policy offering with the growing needs of the clients and qualifying the churn risks, the insurance companies must adopt a structured life-stage progression model. It is recommended by the researchers who conducted studies on insurance consumer lifecycle modelling that policy holders demand for altering their insurance plans in different life stages including marriage, birth of a child, career progression with policy expansion. In these cases, the insurance companies can organize digital and automated campaigns to initiate new offers to newlywed policyholders' incentives for different aspects including spouse-inclusive facility, family planning, maternity coverage. In this case, the insurer becomes the health and financial security partner of the individual in the long-term. The insurance companies can pre-empt disengagement of the policy holders with a clear anticipation of the transitions takes place in different life stages and alternating new offering in the same alignment. With such practices, the companies can be benefited with shaping policy holders' behavior with regular renewal, minimal rate of policy lapse and increased tenure of policy. With the use of personalization strategy, insurers reinforce the engagement of policy holders and value of the policy.

The high-utilization policy holders have increased engagement with insurers due to availing services in medical emergencies, the policy holders who are low-cost have disconnection between expenses in premiums and availed benefits of services. These policy holders seek for updates about policy, effective communication and perceived benefits.

When the insurance companies given personalized guidance to the policy holders at different life stages, the attachment of the policy holders with the insurer increases and they do not intend to switch without seeking for any financial incentives. Considering this, it is vital for insurers to offer AI-driven personalized consultation to the policy holders for giving them reminders for preventive care utilization, incentives for participating in the wellness programs and tailored education content according to the demographic profile of the clients and their behavioral aspects. For example, the insurer's value proposition goes beyond simple financial risk protection, by providing newly enrolled policyholders with personalized onboarding materials that highlight the advantages of preventive screenings, digital health coaching resources, and reminders for their first yearly checkup. With such a strategic approach insurers can ensure cultivating policy holder engagement and reduce the probability of the client switching to the competitors. With the adoption of the mechanism of developing early-stage insurance habit and it should be directed through sustained interaction and drive non-transactional engagement with the policy holders. The elderly policy holders seek for health coverage with financial necessities facing intense medical emergencies, however young policy holders consider that insurance is an optional expenditure for them which is not necessarily utilized by them consistently. Therefore, offering the incentives to keep the policyholders engaged it important for insurers.

Research studies about psychology of habit-formation and modelling of consumer behavior recommend that consumer engagement mechanisms which are reward-based develop stickiness of the policy holders along with offering loyalty incentives in the routine service process. Capitalization of this can be done by insurers through adopting high-engagement mechanisms but cost effective such as digital rewards, wellness gamification, and incentives for tiered participation. This develops a good association between the insurer and policy holder via offering value added services on a regular basis, despite only having financial responsibility in submissive manner. Under value added services, the policy holders can be offered with additional loyalty points when they complete annual health assessment, being involved in the fitness challenges sponsored by insurer and participation in the digital health education webinars and formation of an accrued value system for cultivation of the policy renewable behavior of the clients. The customer-lock-in strategies have alignment with this strategy that are common in the financial sector where accumulation of the value results minimizing the attrition rate through encouraging engagement level of policyholders. The adoption of this engagement model improves retention metrics for the young clients and improves their contribution in the overall revenue stream of the companies and this ensures that acquisition cost is amortized over policy lifecycle extension and facilitates diversification of the risk at the same time. In the case of elderly policy holders, the claims exceed premiums, however in young policyholders' revenue margin is extremely high and assets are low-risk and hence retaining them for long-term proves financially beneficial for the companies.

The insurers have the opportunity to avail benefits of improvement in the portfolio stability, higher profits, and low dependency on price competition trough transition of policyholders from low-premium and single product to high-contribution insureds and multi-tier. Additionally, insurers can set themselves apart from cost-driven commoditization by creating a prolonged engagement ecosystem, which will increase brand loyalty and reduce attrition risks brought on by competitors.

Retaining policyholders who are low-cost and have high-future value outside the criteria of price differentiation and unique policy features, generates a need for a comprehensive framework for customer lifecycle management in optimized manner. This framework will integrate multiple benefits including expansion of benefits at different life stages, customer engagement initiatives which are hyper-personalized and reinforcement of loyalty.

Insurers that successfully implement these data-driven, life-cycle-optimized retention strategies will not only improve policyholder tenure and increase lifetime value (LTV) but also establish themselves as long-term health and financial security partners, ensuring that young professionals transition into high-value, lifelong policyholders rather than transient, churn-prone customers susceptible to price-driven switching behaviors in an increasingly competitive insurance marketplace.

Lastly, low-risk, high-CLV customers, termed "Fortune Makers," are highly valuable and should be prioritized for retention through special incentives and consistent engagement, as they contribute significantly to long-term profitability and family CLV. High-value, long-term policyholders represent an insurer’s most strategically valuable segment, offering consistent revenue, low claims volatility, and significant brand advocacy potential, necessitating a data-driven, relationship-centric approach to customer retention that maximizes customer lifetime value (CLV) while reinforcing trust, emotional engagement, and perceived exclusivity. Unlike transactional or price-sensitive policyholders who frequently engage in competitor-driven churn behaviors, high-CLV customers exhibit intrinsic loyalty and lower price elasticity, making their retention an actuarial and strategic imperative.

Research in financial services loyalty economics and customer relationship management (CRM) theory underscores that long-term policyholders with high retention probability are also the most effective organic brand promoters, reducing customer acquisition costs (CAC) through referrals and reinforcing an insurer's reputational capital within its market segment. A prototypical example would be a business owner who has maintained a premium-tier health policy for over 20 years, rarely files claims, and has referred to multiple employees and peers to the insurer, thereby driving compounded revenue through secondary policyholder acquisition. However, the sustainability of this customer relationship is not solely contingent on passive loyalty but requires a structured, proactive retention strategy that reinforces emotional engagement, intergenerational policy continuity, and predictive, personalized customer interactions.

To achieve this, insurers must integrate three interrelated retention frameworks: loyalty recognition programs, seamless family-based policy transition mechanisms, and advanced behavioral analytics-driven engagement models. First, insurers must implement high-value policyholder recognition programs to reinforce commitment and perceived exclusivity, ensuring that long-term customers feel valued beyond transactional interactions.

Studies in relationship marketing and consumer psychology indicate that customers who receive personalized loyalty acknowledgments are significantly less likely to switch providers, even when competitive alternatives exist, highlighting the role of non-financial engagement in retention sustainability. Deploying the recognition initiatives on the part of insurers is vital for winning customer trust and loyalty including rewards for anniversary, premium-tier wellness benefits and improving brand differentiation. Research in behavioral loyalty economics suggests that reciprocal appreciation, where long-standing customers receive tangible rewards, this enhances the emotional and psychological bond between insurer and policyholder, ultimately strengthening retention rates and mitigating disengagement risks. Second, insurers must establish family-inclusive retention models to ensure multi-generational policyholder continuity, leveraging the inherent inertia associated with intergenerational insurance planning.

Longitudinal studies in insurance policyholder lifecycle analysis indicate that policyholders who transition dependents into their insurer's ecosystem exhibit significantly higher retention rates due to structural continuity factors, wherein the financial and administrative convenience of maintaining a single insurance provider across family generations outweighs competitor-driven price incentives. For example, an insurer could implement seamless dependent-to-individual policy migration programs, offering discounted premium structures when a policyholder's child transitions from family coverage to an independent plan at age 25, ensuring that policyholder loyalty is extended across multiple life stages and not lost at key transition points. Third, insurers must leverage advanced predictive analytics and segmentation frameworks to maintain proactive engagement, ensuring that high-CLV policyholders remain continuously aligned with evolving policy benefits and service offerings.

Unlike transactional customer retention models, which rely on reactive renewal strategies, insurers must deploy machine learning-driven attrition risk assessment tools that analyze behavioral engagement patterns, claim history, and policy utilization rates to identify potential disengagement trends before policyholder churn occurs. Research in predictive consumer analytics and insurance risk modeling highlights that insurers who integrate AI-driven customer segmentation models achieve up to 25% higher retention rates among high-value policyholders, as these frameworks enable personalized, preemptive interventions tailored to policyholder preferences, communication behaviors, and demographic shifts. For instance, insurers could develop policyholder-specific engagement pathways, offering exclusive benefit updates, early-access policy modifications, or concierge health consultations based on individual predictive attrition scores, ensuring that policyholders remain actively engaged with their insurer's ecosystem rather than passively renewing without perceived added value. However, beyond structured retention mechanisms, the sustainability of high-CLV policyholder relationships is intrinsically linked to broader trust and regulatory considerations within the insurance sector, necessitating a comprehensive approach to policyholder confidence, claims settlement transparency, and perceived service reliability.

Research in financial services reputation management underscores that customer trust is the single most critical determinant of long-term policyholder retention, with insurers that engage in opaque claims processing, restrictive policy exclusions, or unexpected premium escalations experiencing disproportionately higher attrition rates and reputational damage (Fombrun & Van Riel, 2004; Pavlou & Gefen, 2004). Unlike other financial services sectors, where customer switching costs are relatively low, health insurance policyholders operate within a complex risk-averse decision-making framework, wherein switching providers involves not only financial costs but also psychological concerns surrounding continuity of care, preferred healthcare provider networks, and claim settlement expectations.

Behavioral research in insurance retention psychology suggests that policyholders who perceive their insurer as a stable, transparent, and customer-centric entity exhibit a significantly lower probability of voluntary churn, reinforcing the importance of predictable pricing models, accessible claims servicing, and seamless policy benefit disclosures in high-CLV customer retention strategies. It is important to comprehend by the policyholders that client switching cost is not cost driven only but embedded in the cognitive friction also where service reliability of a new insurer and associated uncertainty is weighed by the policy holder in opposition to the familiarity with existing service providers and this results into enhancement of unified consumer engagement, policy renewal without any hassle and getting expected benefits. Insurance companies can reformulate their customer retention strategies via embedding AI-driven consumer engagement policies, segmenting customers on behavioral category and modelling based on risk propensity. With the integration of advanced machine learning algorithms in the CRM strategy for identification of the policyholders who are prone to disengagement risks and intervening in a timely manner for prevention of customer attrition rate. Among policyholder having high value maximizing CLV proves the most contributing factor for generation of increased revenue rate. This is because retention of the high-CLV policy holder is significantly more cost-effective than acquiring a new customer through traditional marketing and distribution channels.

Unlike short-term customer acquisition models, which prioritize new policy sales at the expense of long-term retention investments, insurers must recalibrate their strategic focus toward building deep-rooted, relationship-driven policyholder engagement frameworks that prioritize lifetime customer value over initial premium volume. In an increasingly data-driven, digitally integrated insurance ecosystem, insurers that successfully implement personalized loyalty programs, family-centric retention models, and predictive customer engagement technologies will not only strengthen policyholder tenure and optimize CLV but also future-proof their market positioning in a competitive, highly regulated, and evolving health insurance landscape.

Ultimately, the question for insurers is no longer simply how to acquire high-value policyholders but rather how to retain, maximize, and continuously enhance their value through predictive, personalized, and trust-driven retention mechanisms that ensure sustainable profitability and long-term policyholder advocacy.

We use a multi-objective approach as outlined in Figure 3 that combines model-free evidence with a commitment to upholding the company’s values and prioritizing customer well-being.

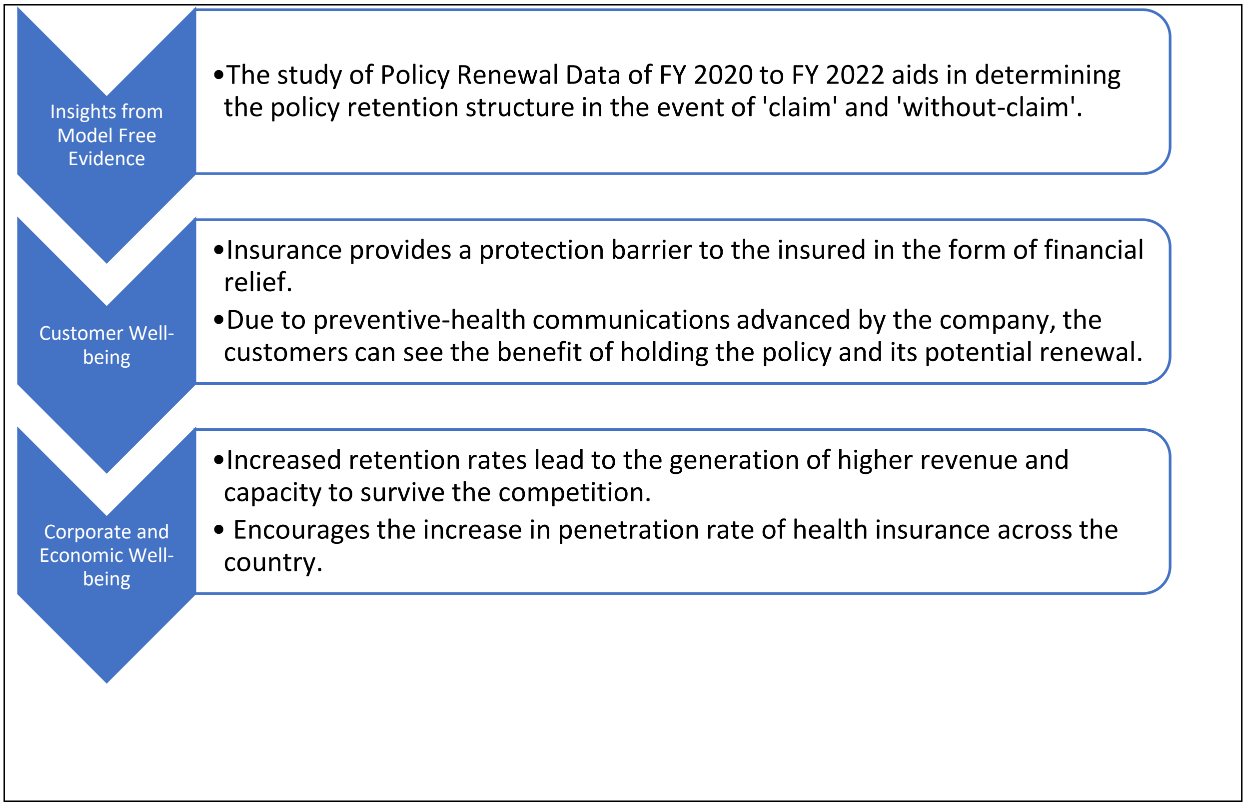

Figure 3 multi-objective approach.

In the context of an increasingly competitive insurance market, understanding the factors that drive customer retention is paramount for insurers seeking to sustain long-term profitability and customer loyalty. Prior research suggests that policyholder behavior, insurer communication strategies, and household-level decision-making play a crucial role in influencing renewal and retention patterns. Drawing upon these theoretical foundations, this study posits three key hypotheses that explore the dynamics of claim incidence, insurer communication, and intra-household insurance choices.

H1: The Incidence of an Insurance Claim Positively Influences Renewal Retention in Health Insurance

This hypothesis asserts that customers who experience an insurance claim event are more likely to renew their health insurance policies. The underlying rationale is that claimants, having engaged directly with the insurer's claims process, gain a tangible appreciation of the policy's utility, thereby reinforcing their perceived value of coverage. Prior research in consumer behavior suggests that firsthand experience fosters cognitive reinforcement, reducing uncertainty and enhancing trust in the insurer's reliability. Furthermore, claimants who receive favorable claim settlements may develop a sense of commitment or psychological contract with the insurer, further increasing the likelihood of renewal.

H2: Proactive Health Communication (PHC) by Insurers Enhances Policyholder Retention

This hypothesis posits that structured and strategic health-related communication from insurers, such as wellness reminders, preventive care guidance, and personalized engagement, contributes to higher retention rates. Effective PHC serves a dual function: first, it nurtures a sense of continuous engagement, ensuring that policyholders perceive ongoing value beyond just claims reimbursement; second, it mitigates information asymmetry by providing policyholders with timely and relevant insights that enhance their ability to make informed health and financial decisions. Theoretically, this aligns with relationship marketing and customer engagement frameworks, which argue that sustained, value-added communication strengthens consumer-brand relationships and fosters long-term loyalty.

H3: The Occurrence of a Claim in a Household Increases the Likelihood of Dependent Family Members opting for the Same Insurer

This hypothesis is grounded on the diffusion of insurance decision in the household. As per the hypothesis, in the case of filing a claim by any policyholder, all the dependent members of the same family also prefer to opt the same insurance company. Risk perception theory is the main grounded theory of this phenomenon where individuals have a high degree of reliance on the people in their proximity, most specifically the family members while taking financial decisions involving high risk. When the claim of insurance is settled in a household satisfactorily it develops the trust of other family members on the insurer and thus it works as a referral for other dependents because they have reduced cost of transaction and minimum perceived uncertainty of switching to the other insurance service provider. Substantiating this hypothesis in empirical manner, in the subsequent section defined the methodology approach and data used for hypothesis testing. In this research, statistical model is applied for quantifying causal relationship for gaining knowledge about the insurer strategy for optimization of customer retention and winning competitive position in the health insurance industry.

Data

The data is collected from an Indian insurance company deals in private insurance. The study spans various hypotheses, covering the data period from Financial Year (FY) 2018 to 2023. For Hypothesis 1 (H1), the decision tree data from FY 2018 to FY 2022 is considered, while for Hypotheses 2 (H2) and 3 (H3), data from FY 2019 to FY 2023 is utilized. This distinction in the data period coverage is determined by the specific requirements of each hypothesis and quasi-experimental considerations during the study process. In FY 2018, the total base policies amounted to 7,63,026.

We employ a model-free evidence mechanism for the FYs 2020, 2021, and 2022 to differentiate between insurance policies with and without claims. The insights gathered from the model-free evidence guided us to conduct the quasi-experiment in FY 2023. As part of this experiment, data related to Preventive Health Checkup (PHC) was studied from FY 2019 to FY 2023, focusing on its relation to filed claims and its impact on retention rates.

The trends in PHC reflected in Figure 4 highlights an increase in the total renewal base from 0.4% in FY 2019 to 1.8% in FY 2023. Additionally, instances where PHC was undertaken showed a 7-8% increase in customer retention rates compared to instances where it was not undertaken.

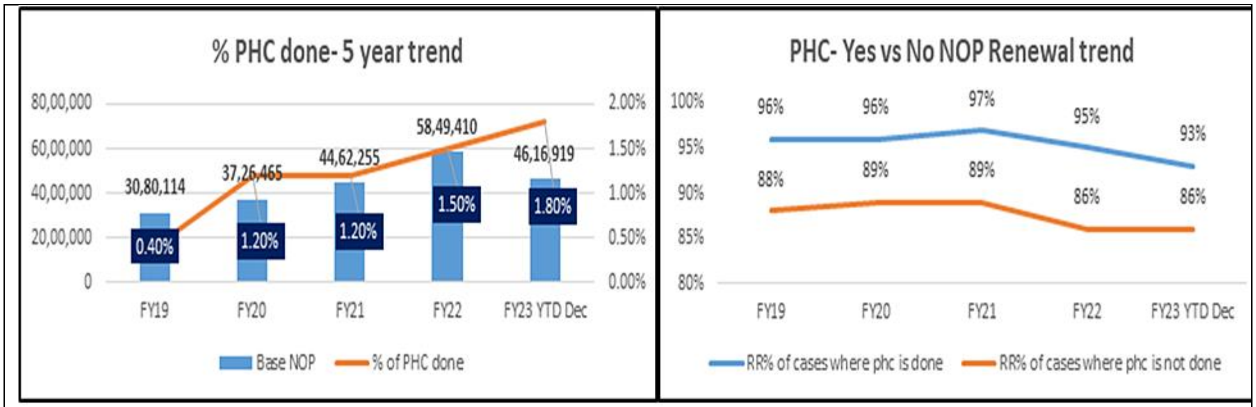

Figure 4 PHC Trends and adoption.

Through this data design, the Quasi-experiment involved identifying the customers who did not file any claims. By leveraging Thaler's nudge theory, the company induced claim among its policyholders by improving communication regarding PHC. This approach enabled us to examine the effects of PHC on the customer retention rate. To systematically analyze these effects, the following section outlines the research methodology employed in this study.

Research Methodology

3.1 Model-Free Evidence

Figure 5 shows the model-free evidence which forms a crucial foundation for this study by providing justification for the conceptualization and development of

	CUSTOMER RETENTION SUMMARY						
		FY 20		FY 21		FY 22	
	PAID STATUS- SINCE INCEPTION	COUNT	RETENTION RATE	COUNT	RETENTION RATE	COUNT	RETENTION RATE
POLICIES WITH CLAIMS	Total NOP renewed	1599285	95.45%	1767459	95.53%	1917843	93.48%
	total renewal-able base	1675595		1850067		2051560	
POLICIES WITHOUT CLAIMS	Total NOP renewed	1696047	82.81%	2202881	84.33%	3103850	81.74%
	total renewal-able base	2048194		2612193		3797269	
	Total renewed	3295332		3970340		5021693	
	Total nop Due for renewal	3723789	88.49%	4462260	88.98%	5848829	85.86%

Figure 5 Model Free Evidence

Utilizing data from the three-year period (FY 2019 to FY 2022), we observed the pattern of PHC claims along with the changes in the retention rates. The process involved identifying the number of policies due for renewal, the actual number of renewals, and calculating the retention rate for each FY. This exercise revealed a significant disparity in renewal rates between policyholders who filed claims and those who did not. Specifically, policyholders with claims were more likely to renew their policies compared to those who did not file any claims. Overall, the pattern of PHC claims' data guides us to undertake quasi-experimental research to examine if the induction of claims through effective PHC communication leads to higher policy renewal rates. Employing a quasi-experimental approach in this context allowed for a structured evaluation of behavioral responses, providing deeper insights into the causal relationship between PHC engagement and customer retention.

3.2 Quasi Experiment

Quasi-experiments are widely used in marketing research to evaluate the causal effects of marketing strategies and interventions when randomized controlled experiments are not feasible (Goldfarb et al., 2022). We conduct a quasi-experiment where policyholders receive communications promoting Preventive Health Checks. Figure 6 summarizes the communication modes and processes undertaken to induce the anticipated artificial claims/claim like situation among the policyholders.

User Journey / Life cycle Steps	User Action	Timelines	Communication Mode (SMS)	Conversion Rate (SMS)	Communication Mode (WA)	Conversion Rate (WA)
After Policy Purchase	User Purchases the policy	On the same day	Good News ! You have just unlocked a Free Preventive Health Checkup with your recent policy purchase... [Deep Link]	10%	Good News ! You have just unlocked a Free Preventive Health Checkup with your recent policy purchase... [Deep Link]	40%
	User does not avail PHC till 7 days	7th day	Reminder: Take advantage of your Free Preventive Health Checkup with your [Health Insurance Policy]...[Deep Link]	5%	Hello [Name], Hope this mail finds you well...[Deep Link}	20%
	User still hasn't availed PHC post 7 days	Every 20th day	NA	5%	Hi [Name], This is [Health Insurance]. Just a quick reminder about the Free Preventive Health Checkup...[Deep Link]	15%
		Every 15th day	Reminder: Take advantage of your Free Preventive Health Checkup with your [Health Insurance Policy]...[Deep Link]	5%	NA	10%
After Policy Renewal	User Renews the Policy	On the same day	Congratulations ! You have just unlocked Complementary a Free Preventive Health Checkup with your policy renewal... [Deep Link]	10%	Good News ! You have just unlocked a Free Preventive Health Checkup with your policy renewal... [Deep Link]	35%
App Install	User Installs the App (But doesn't use PHC	On the same day	Welcome to [Power] ! To help you to get ted, we're offering a Free Preventive Health Checkup with your Insurance Policy... [Deep Link]	8%	Welcome to [Health Insurance] !, To help you to get ted, we're offering a Free Preventive Health Checkup with your Insurance Policy... [Deep Link]	25%

Figure 6 Messaging across-User journey/Lifecycle steps.

Included in this procedure are the "After Policy Purchase," "After Policy Renewal," and "After Application Installation" stages of the user experience, where data is used to establish the distribution of timings and channels of communication for efficient nudging.

Regulatory Focus Theory (Prevention- and Promotion-focusses) and Nudge Theory are used to develop carefully worded messages that provide new and current policyholders a free preventive health check-up under different user journeys. The goal is to improve adoption. Regulatory fit theory and nudge theory are utilized to develop communications connected to PHC with an emphasis on prevention and promotion. Consumers were educated about the advantages of PHC via communications in the prevention-focused approach. Informational nudging included drawing attention to the fact that their coverage covers PHC, value-based nudging included stressing the importance of the company's dedication to its customers' health and wellbeing, and incentive-based nudging included providing services to encourage consumers to make use of this provision. By highlighting the ways in which health insurance might lessen financial burdens in the event of a health emergency for the insured and their dependents, messages conveying the advantages of policy renewal were part of the promotion-focused strategy.

Customers with high-risk characteristics, such as diabetes, hypertension, cardiac indicators, or high body mass index (BMI), are enrolled in a voluntary program called the Condition Management Program (CMP) once data obtained after Primary Health Care (PHC) intervention is analyzed. In order to motivate these clients to enhance their health, a tailored strategy is developed for them. Overall loss ratios are expected to be favorably affected by the program's goal of improving customer well-being and lowering their risk profile. In addition, policyholders who follow the program's rules are eligible for wellness incentives, which translate to lower rates. Not only does this method aid in bettering consumer health, it also significantly contributes to customer retention.

The purpose of this experiment is to test hypothesis 2 by using an XGBoost Classifier to see whether, in a claim-like situation, consumers are made more aware of possible future health hazards as a result of good PHC communication. Everything about a PHC visit is eerily similar to a real one, down to the smell of medical equipment, the feeling of needles in the skin, and the nervous anticipation of test results. These components work together to mimic the mental and administrative aspects of a future claim, which may affect how customers see the product and, in turn, increase the likelihood that they will renew their insurance. The next section details the communications techniques put into place at various points in the user experience and policyholder lifecycle to make this strategy work.

Aligning communication strategies, behavioral nudges, and decision architectures with consumer psychology and decision-making heuristics, the health insurance sector can apply Regulatory Focus Theory (RFT) and Nudging Theory strategically. This framework is scientifically grounded and empirically validated, and it can optimize customer engagement, increase policyholder retention, and enhance long-term profitability. There is strong evidence from WhatsApp engagement strategies that interactive, rich-media messaging increases conversion rates across various customer touchpoints, especially during policy purchase, renewal, and preventive health checkup (PHC) utilization stages. This supports the idea that personalized, urgency-driven communication is important for proactive customer engagement.

The significance of personalized, behavior-based communication tools in shaping customer actions is highlighted by the fact that response rates are greatly enhanced when personalized messages include the policyholder's name, policy status, and real-time reminders about benefits that are about to expire or go unused. The most important times to reinforce the benefits of PHC are during the policy purchase and renewal stages. To achieve this, you need a multi-tiered, lifecycle-driven messaging strategy that starts early (immediately after purchase), continues with reminders, and uses incentive-based reinforcement to keep policyholders engaged over time and encourage PHC adoption during these decision points. Studies in consumer decision-making science, behavioral economics, and cognitive load theory highlight the importance of timely, proactive interventions that use social proof, habit formation, and default mechanisms to increase customer retention rates, decrease policyholder drop-off rates, and increase long-term health insurance benefit utilization.

Regulatory Focus Theory (RFT) and Nudging Theory come together to provide a paradigm for influencing policyholder behavior that is dual-perspective and behavior-segmented. Customers driven by ambition, incentives, and self-improvement are more receptive to incentive-based campaigns that emphasize the advantages of financial stability, complete coverage, and preventative healthcare. Customers that are prevention-focused and value safety, risk reduction, and avoiding negative outcomes are more likely to respond favorably to advertisements that emphasize financial security during health crises, reduce out-of-pocket healthcare costs, and protect against medical emergencies.

The application of motivation driven approach proves directive for the insurers to get benefited from high-rate policy renewal, enhanced loyalty of policyholders and high consumer engagement. In the selection of choices of health insurance policies, choice architecture is shaped by nudging theory and even without compromising with the independence of consumers, the reduction of cognitive overload and easy accessibility of plan choice and high rate of consumer enrollment. This theory is complementary to consumer segmented based on RFT and proves supportive for consumer decision making process.

Past research studies conducted in relation to behavioral decision science and default effect theory affirms that most of the people tend to go with selecting insurance plans rather than having active selection of choices and this minimizes the level of voluntary churn and facilitates policy renewal in automated manner. Higher insurance renewal rates and long-term retention are ensured by using default alternatives, where automated enrolment methods significantly boost participation by taking advantage of consumer inertia.

Furthermore, there are two core benefits of using an optimized decision-making framework including higher perceived value and increased consumer engagement through keeping the health coverage options limited and using a simple architecture of insurance plan defining cost-benefit trade-offs in transparent way. This approach proves supportive in minimizing fatigue in decisions and enhance satisfaction level of policy holders.

This is evident from empirical data findings that confidence level and conversion rate of policy holders is driven through most common policy alternatives and adoption trend of other known people as this gives a behavioral motivation to individuals. With these findings it is affirmed that consumer purchase decisions are directly affected by group decision making that has a direct psychological impact.

Nudging theory affirms that for improved consumer engagement promoting healthy behavior among consumer, multiple motivational drivers are responsible including offering discounts on premium for preventive care, use of wellness incentives and gamification model. With the help of these initiatives the firms enable them to minimize the claim cost and increase the rate of retention of policy holders in the long term. Gaining multiple benefits such as rewards, incentives and behavioral reinforcement enhances the engagement level of the policyholders. With this a habit-forming eco-system can be developed for enhancing affinity of the stakeholders and minimizing the risk of high attrition. The interaction between Nudge theory and RFT ensures the active engagement of the policy holders with the insurance company because this influences decision making behavior of the policy holder and enhancement of retention rate and improved level of client satisfaction. For such purpose, the firms develop retention strategies which are driven through customer loyalty. For the financial year 2020-2022, the policy renewal data supported by Service-Profit Chain model shows that retention policies which are claim based are supportive for ensuring customer loyalty, customer satisfaction and high profitability (Heskett et al., 1994). When the claims process takes place with high trustworthiness and transparency results in client attrition rate in the post-claim phase and even enhances degree of customer satisfaction as when the submitted claims by the customers are cleared it develops happiness from the service receival.

Some policyholders have high inclination to policy renewal as they do not file claims because these policies do not have any claim-bonus structure, minimal health risks for future and policy inertia related psychological effect. These findings have a direct alignment with prospect theory according to which decision assessment by individuals is done considering comparative profits and losses irrespective to the absolute usefulness of the health insurance coverage. Hence, there is extraordinarily little tendency of policy holders to switch to the other insurers, who do not file any claims in their policy considering the condition that they are satisfied with their policy provisions (Samuelson & Zeckhauser, 1988).

The two key segments of policyholders are claim active and claim free and accordingly the data-driven engagement strategies are formulated by the insurance companies for winning loyalty of the policyholders via offering them varied personalized benefits, loyalty rewards, special benefits to claims free customers and hence with their trust and engagement. In such a process, measures like effective communication, fast claim settlement process contributes to rebuild the customer confidence and trust and reduce the propensity of the post-claim churn. The ability of insurers towards identification of high-risk attrition is driven through multiple factors including predictive analytics, behavioral segmentation and machine learning algorithms. This facilitates the insurers to place strategies of pre-emptive engagement for churn removal. The insurers can develop hyper-personalized retention model through provision of multiple claims offers, sentimental analysis of policy holders and digital interaction with customers. This model directs to have engagement of the policy holder in an optimized manner and maximizing CLV and hence making the client portfolio stable in the long run. Additionally, the inclusion of AI-driven customer segmentation, deep-learning behavioral prediction models, and personalized digital intervention frameworks enables insurers to proactively identify at-risk policyholders and deploy tailored engagement strategies, ensuring that policyholder retention initiatives are not merely reactive but predictive and pre-emptive in nature.

Digital transformation has fostered rapid changes in the insurance sector and regulatory compliance and changes in the expectations of the policy holders, using interdisciplinary framework, insurance companies can gain benefits using data-driven consumer engagement considering the multiple theoretical considerations including cognitive decision-making and behavioral economics. Adoption of this framework enables the firms to have retaining policy holders in an optimized manner, policy renewal in favorable manner and ensuring business financial sustainability. The insurances companies that take into consideration multiple aspects of behavioral science in different functional areas including interaction with policy holders, management of policy claims and CRM strategies gain benefits of increased rate of customer retention and ensure their long-run competitive position in the present insurance ecosystem which is highly regulated, data driven and customer focused.

A paradigm shifts in the way insurers approach policyholder retention can be seen in the convergence of Regulatory Focus Theory, Nudging Theory, predictive analytics, and behavioral segmentation. This shift is from traditional reactive renewal models to a proactive, data-informed approach that guarantees long-term engagement, sustainable profitability, and optimized customer lifetime value. In this changing insurance landscape, insurers must now consider how best to use behavioral insights, AI-driven segmentation, and nudging mechanisms to create a smooth, loyalty-driven insurance experience that builds policyholder trust, reduces churn, and maintains long-term growth in a market that is becoming more competitive and technologically advanced. To further develop this prediction technique, the following part goes into the modelling framework. While many approaches were tried such as Logistic Regression and based on the results, we finalized the XG boost Classifier to assess important retention trends.

Modeling

XGBoost Classifier

Gradient boosting aims to construct an approximation, F(x), of the function f(x), which relates input instances x to their corresponding output values y. This is achieved by iteratively minimizing the expected value of a specified loss function L (y, F(x)) using a training dataset $\{(x_i, y_i)\}$. The method builds F(x) as a weighted sum of functions $h_i(x)$, where each $h_i(x)$ represents a model in the ensemble (e.g., decision trees). Initially, a constant approximation of f(x) is obtained. Subsequent models are added to improve the fit by minimizing the residuals of the previous iterations. Instead of directly solving this optimization, each new model $h_i(x)$ is trained on a modified dataset where the pseudo-residuals r_{i-1} guide the learning process. The weight γ_i for each model $h_i(x)$ is determined through a line search optimization to minimize the overall loss function. According to Friedman (2001), if the iterative process of this algorithm is not adequately regularized, it may lead to overfitting.

XGBoost (Extreme Gradient Boosting) is a popular implementation of Gradient Boosting Decision Trees, known for its scalability in machine learning. It consistently achieves cutting-edge results across diverse problem areas. As a result, XGBoost shows promise in addressing large-scale real-world problems with minimal resource usage (Chen & Guestrin, 2016). By minimizing a predetermined loss, XGBoost builds an iterative enhancement of the objective function F(x), much like gradient boosting. XGBoost only uses decision trees as base classifiers, in contrast to other approaches. Bentéjac et al. (2021) claim that XGBoost uses a number of methods to speed up decision tree training without compromising ensemble accuracy. They point out that XGBoost employs techniques designed to expedite decision tree training, with a special emphasis on lowering the computational complexity associated with choosing the optimal splits.

In XGBoost the base learner is a decision tree. The decision trees are developed in an iterative manner where in subsequent trees, the errors found in the past trees are overcome. XGBoost apply the technique of gradient boosting where loss function gradients relative to the predictions are used for providing the base for constructing the successive trees. XGBoost gains learning from previous errors and enhances performance iteratively. In research studies conducted about customer retention and churn prediction, XGBoost is well known for management of intricate datasets and predictive modelling.

Another study conducted by Lalvani et al. (2022) reflected that XGBoost Classifier, CatBoost Classifier, AdaBoost Classifier, Extra Tree Classifier, Naïve Bayes, Support Vector Machines, Decision Trees, Random Forest, and Logistic Regression were among the well-known machine learning techniques evaluated in a comparative study of customer churn prediction in the telecommunications sector. Among these techniques, the XGBoost Classifier performed better, with an accuracy of 80.8%.

In a similar context, Li et al. (2024) affirmed genetic XGBoost's enhanced version for making customer consumption behavior prediction and its main focal area is enhancement of accuracy in the predictions via optimization of the parameters of XGBoost.

Another study conducted by Fauzan and Murfi (2018) in the auto-insurance sector focused on improvement of the accuracy of the prediction of the insurance claims made by XGBoost. The study findings proved supportive to demonstrate that XGBoost in the process of normalizing the Gini accuracy metrics outperform. In order to forecast and reduce telecom customer attrition, Patel and Kumar (2023) examined the aspects that contribute to it and created a machine learning model. Among the studied algorithms, XGBoost had the best accuracy of 94%, demonstrating its potency in churn prediction. They pointed out that XGBoost is perfect for big datasets due to its quick training times and resilience in handling missing data, providing telecom businesses with a dependable tool to proactively detect and keep at-risk clients. Motivated by existing research and proof of its precision, we employ the XGBoost Classifier in our investigation.

Modeling Results

Our research shows how well the XGBoost classifier can be used to analyze and forecast insurance policyholders' customer retention based on whether or not they have filed a claim. Using the data from the first objective, the XGBoost Classifier yields intriguing results with an accuracy rate of 64% and a precision rate of 82%. The following variables are included in the model: the amount insured, the number of policyholders who declared a pre-existing condition (PED), the vintage, the product grouping, the reported claim count in year t-1, the paid claim count in year t-1, and the rejected claim count in year t-1.

Although retention was measured against this sample, for the purpose of analysis, we employed a 60-40 distribution in our sampling.

This approach ensures that all observations have an equal opportunity to be predicted accurately in the absence of sufficient information to predict success or failure.

Table 2: Total number of policies against the number of claimed years and their vintage from FY 2018 to FY 2022

No of claimed years	FY 18	FY 19	FY 20	FY 21	FY 22
0	710001	500796	397490	316344	254762
1	53025	79120	104465	123347	124876
2		11707	23435	38058	49397
3			3956	9905	16535
4				1904	4913
5					1038
Grand Total	763026	591623	529346	489558	451521

In this first step of analysis, we observe that there are 1,038 policies that have at least one claim in the specified 5 FYs. Furthermore, 33% (i.e., 2,54,762) of total base policies did not make a claim across vintage, while 16% (i.e., 1,24,876) of total base policies show a claim in at least one of the years across the vintage.

Table 3: Renewal of policies across the vintage

No of claimed years	FY 18	FY 19	FY 20	FY 21	FY 22
0	710001	500796	397490	316344	254762
Renewed %	77%	89%	92%	92%	77%
1	53025	79120	104465	123347	124876
Renewed %	81%	91%	93%	92%	78%
2		11707	23435	38058	49397
Renewed %		90%	94%	93%	79%
3			3956	9905	16535
Renewed %			93%	93%	80%
4				1904	4913
Renewed %				93%	80%
5					1038
Renewed %					81%
Grand Total	763026	591623	529346	489558	451521
Renewed %	78%	89%	92%	92%	78%

Overall, as the vintage increases, the renewal rate for policies that have been claimed stabilizes in comparison to non-claimed policies. Specifically, FY20 and FY21 show high renewal rates of 92%, respectively, which can be attributed to the influence of the global pandemic on customers' perceptions of securing health insurance benefits. However, in the subsequent financial year of 2022, there is a noticeable decline in the renewal rate to 78%, indicating that policyholders may have been influenced in their renewal decisions due to their individual experiences of claim submission or not.

The decision tree presented in Figure 7 illustrates the year-on-year distribution of policies categorizing them based on the presence or absence of Pre-Existing Diseases (PED). The tree branches to differentiate between policies with claims and those without, further distinguishing between renewed and non-renewed policies.

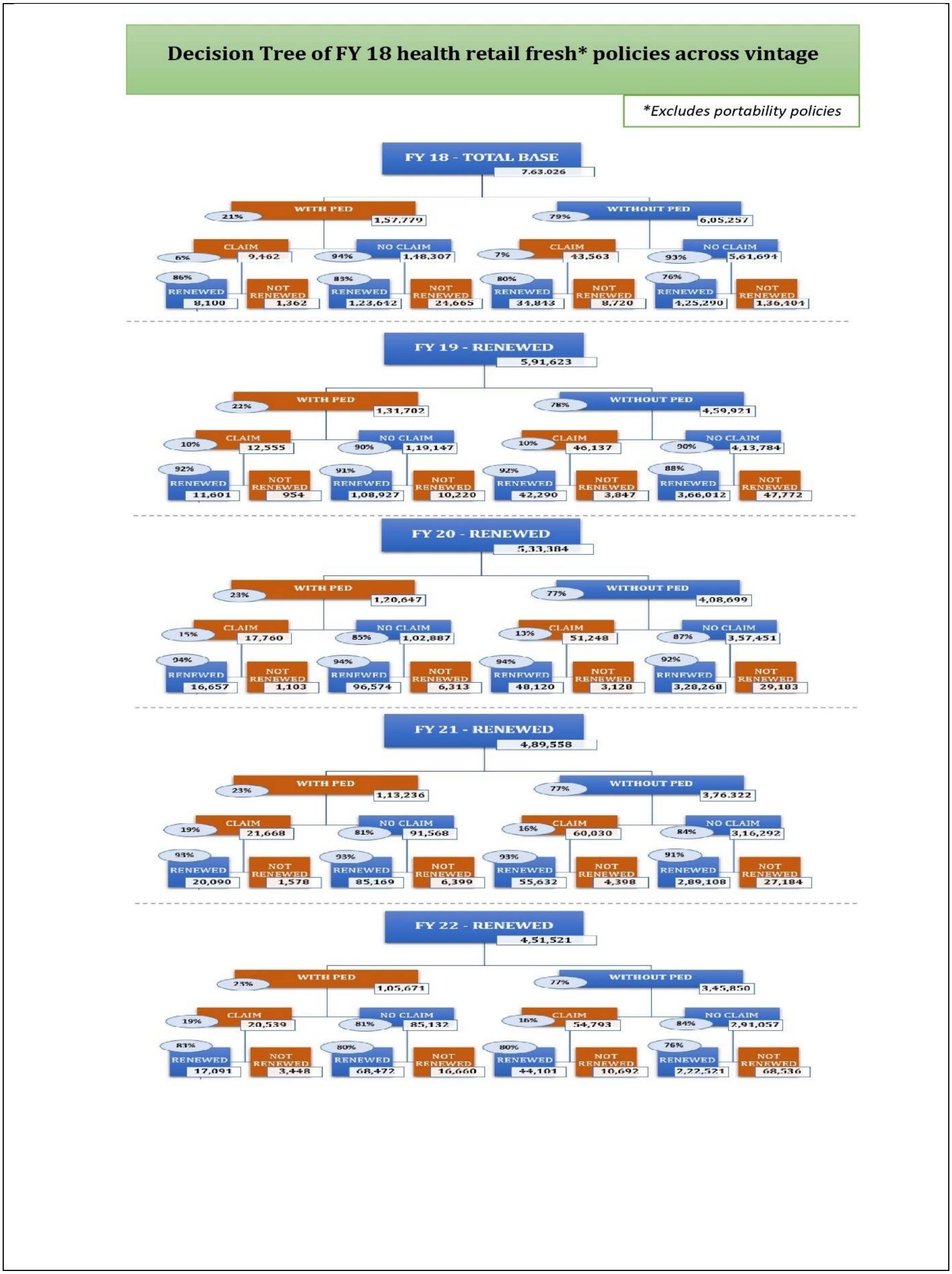

Figure 7 Decision tree of policies starting FY 2018

The base data beginning from FY 2018 has a Matrix of 79% of the insured having PED and 21% not having a PED. Retention rates for first year and second-year policies are the lowest, primarily because customers often perceive minimal engagement and value during these early stages. In the following studied years, FY 2020 witnessed a high rate of 94% policyholders both with and without PED who made a claim.

On average, policyholders who did not make a claim in the year have resorted to fewer renewals in comparison to those who made a claim. In the final year of the study FY 2022, there is noticeable decline in the renewal rates, among both claimed and non-claimed policyholders. Hence, we accept H1, as the results demonstrate that the incidence of insurance claims significantly impacts the renewal retention of policyholders. Moreover, this finding, along with model-free evidence, motivates us to conduct a quasi-experiment. This experiment involves delivering preventive health check (PHC) communications to customers to stimulate artificial claims and analyze their overall renewal behavior. The subsequent analysis examines key metrics, including the total number of claims from FY 2018 to FY 2022, policy renewal trends across different vintages, and the decision tree of policies initiated in FY 2018.

This quasi-experiment is the first of its kind in India's insurance industry, offering valuable insights into its effectiveness. To assess the impact of PHCs on customer retention, we analyze data from FY 2019 to FY 2023. XGBoost classifier achieved an accuracy of 71% using a 60-40 sampling distribution. The model demonstrated precision and recall rates of 83% and 81%, respectively. The model comprises of these variables: count of claims paid through non-networked hospital in year t-1, count of reported medical claim in year t-1, sum paid in medical claims in year t-1, count of payment through networked hospital in year t-1, reimbursement rejected claim count, reported claim count in medical claims since inception, count of pain claims through networked and non-networked hospitals in year t-1.

To further explore this trend, the following section examines PHC claimed policies, their contribution to total claims, the number of PHC claimed policies with in-patient claims, the rate of in-patient claimed policies relative to total PHC claimed policies, and the proximity of PHC claims to the renewal date in relation to the renewal retention rate.

Tables 4 and Table 5 present the total number of policies that have made claims for PHC, showing its growth across the studied financial years and policy tenures.

Table 4: PHC Claimed Policies

FY	FRESH	1	2	3	4	5	6	7	8	ABOVE 8	Grand Total
FY 19	12	1597	1566	3646	2059	1326	1056	1187	653	624	13726
FY 20	10	9740	8602	8237	5551	3299	2166	1940	1872	1776	43193
FY 21	23	13812	10087	9932	6351	4098	2468	1597	1390	2556	52314
FY 22	132	22007	17521	13854	11522	7472	4741	2958	2051	4937	87195
FY 23	1008	38964	21976	16907	13539	11093	7323	4818	2930	7193	125751

Table 5: Contribution of Total PHC Claimed Policies

FY	FRESH	1	2	3	4	5	6	7	8	ABOVE 8	Grand Total
FY 19	0%	12%	11%	27%	15%	10%	8%	9%	5%	5%	100%
FY 20	0%	23%	20%	19%	13%	8%	5%	4%	4%	4%	100%
FY 21	0%	26%	19%	19%	12%	8%	5%	3%	3%	5%	100%
FY 22	0%	25%	20%	16%	13%	9%	5%	3%	2%	6%	100%
FY 23	0.80%	31%	17%	13%	11%	9%	6%	4%	2%	6%	100%

These analyses reveal a decline in PHC claims from policies in their 3rd and 4th years during which the PED provisions kicks-into the policy, while claims from policies in their 1st and 2nd years have shown a significant increase. It is important to note that although PHC-related claims were included in the data from previous years, the company's strategic promotion of PHC to test and improve retention rates began only in FY 2021. Therefore, the results of PHC claimed policies in FY22 and FY23 reflect the extended management strategy supported by this quasi-experiment. Table 6 and Table 7 represent the two cohorts of PHC as a proportion of in-patient claims and the total claims.

Table 6: Number of PHC Claimed Policies with In-Patient Claims

FY	FRESH	1	2	3	4	5	6	7	8	ABOVE 8	Grand Total
FY 19		61	109	377	230	147	102	128	71	86	1311
FY 20		539	777	768	561	328	188	213	215	206	3795
FY 21	3	688	809	761	517	346	232	132	152	274	3914
FY 22	7	1530	1832	1424	1151	745	514	339	244	578	8364
FY 23	79	2749	2290	1682	1387	1189	775	533	282	834	11800

Table 7: Rate of In-Patient Claimed Policies to Total PHC Claimed Policies

FY	FRESH	1	2	3	4	5	6	7	8	ABOVE 8	Grand Total
FY 19	0%	4%	7%	10%	11%	11%	10%	11%	11%	14%	10%
FY 20	0%	6%	9%	9%	10%	10%	9%	11%	11%	12%	9%
FY 21	13%	5%	8%	8%	8%	8%	9%	8%	11%	11%	7%
FY 22	5%	7%	10%	10%	10%	10%	10%	11%	12%	12%	10%
FY 23	8%	7%	10%	10%	10%	11%	11%	11%	10%	12%	9%

The values indicate that there has been an increasing trend in PHC claims during the first 1 to 4 years, followed by a decreasing trend thereafter. Additionally, significant stability in the number of claims begins from the third year of holding the policy. The data shows a substantial reduction in in-patient claims when policyholders undertake PHC. This observation implies that the diagnostic results from PHC may prompt policyholders to take precautions and preventive measures towards their health. This, in turn, leads to a more favorable health outlook from the policyholders' perspective and retained earnings within the company from the insurance companies' standpoint.

From the Table 8 identifies the proximity and propensity of renewal after PHC. It is observed that as policy maturity approaches within the 0 to 90 days threshold, policyholders who make PHC-related claims, regardless of whether prompted or not, tend to renew their insurance policies with the company.

Table 8: Proximity of PHC claim from renewal date with renewal retention rate.

FY	PROXIMITY	Fresh Policies	1st year policy	2nd year policy	Total Policies
FY 19	0 TO 90 DAYS	100%	95%	93%	96%
	91 TO 180 DAYS	0%	96%	93%	95%
	181 TO 270 DAYS	0%	92%	93%	95%
	ABOVE 270 DAYS	0%	96%	88%	96%
TOTAL		91%	96%	93%	96%
FY 20	0 TO 90 DAYS	100%	96%	97%	97%
	91 TO 180 DAYS	0%	96%	95%	96%
	181 TO 270 DAYS	0%	94%	95%	96%
	ABOVE 270 DAYS	50%	94%	95%	95%
TOTAL		**75%**	**95%**	**96%**	**96%**
FY 21	0 TO 90 DAYS	100%	96%	97%	97%
	91 TO 180 DAYS	50%	94%	95%	96%

	181 TO 270 DAYS	33%	95%	96%	96%
	ABOVE 270 DAYS	100%	94%	96%	96%
TOTAL		80%	95%	96%	97%
FY 22	0 TO 90 DAYS	80%	93%	94%	95%
	91 TO 180 DAYS	82%	93%	93%	95%
	181 TO 270 DAYS	100%	93%	94%	94%
	ABOVE 270 DAYS	33%	92%	93%	93%
TOTAL		79%	92%	94%	95%
FY 23	0 TO 90 DAYS	84%	92%	93%	93%
	91 TO 180 DAYS	80%	91%	92%	93%
	181 TO 270 DAYS	80%	90%	92%	92%
	ABOVE 270 DAYS	77%	89%	91%	92%
TOTAL		81%	90%	92%	93%

This suggests that companies should consider triggering PHC reminders towards the end of policy terms to encourage renewal.

During the quasi-experimental period (FY 22 to FY 23), there was a notable increase in the contribution of total PHC claims. Furthermore, the data suggests a significant impact of PHC claims on the renewal retention rate observed from FY 20 to FY 23. These findings support the acceptance of H2, indicating that PHC communications lead to higher retention rates.

The company acknowledges that while the experiment initially required short-term spending on customer wellness and prevention, the long-term benefits are clearly favorable. As a result, these costs will be viewed as long-term investments in the future. The company regards the experiment as a success and plans to integrate this approach into its customer retention strategy. Additionally, the results indicate that policyholders prompted with prevention-focused communications tend to utilize the offer and recognize the benefits of their policy, thereby encouraging them to renew their policies.

Family Customer Lifetime Value (Family CFV) is a relatively new concept with limited research on the effects of company-directed retention efforts aimed at influencing family members to choose the same insurance provider. We utilize the XGBoost Classifier to analyze scenarios where dependent children, upon reaching 25 years of age, take out new policies for themselves from the same insurance company as their parents. The data utilized for modeling spanned from FY 2019 to FY 2023 and included parameters such as maximum age of members, insurance premium, vintage, number of members with PED, Amount paid since inception through networked hospital, cashless paid amount since inception, Risk count (number of people covered in the policy), number of years the policy has run with the company. The sampling for analysis was split evenly with a 50-50 distribution for training and testing the model, achieving an accuracy of 70%. This distribution ensures equal prediction opportunities for all observations in the absence of prior information on success or failure. Additionally, the model achieved a precision-recall trade-off of 55% after testing multiple probability thresholds.

Our analysis focuses on identifying whether dependents aged 25yr have taken separate policies during renewal for floater policies. Table 9 illustrates the trend of policies with dependent children Aged 25 and no claim conditions.

Table 9: NUMBER OF POLICIES WITHOUT CLAIMS

BASE NOP WITH 25 YEAR CHILD				RENEWED WITH MORE THAN 1 NEW POLICY					
FY	FEMALE	MALE	Total	FEMALE	MALE	Total	FEMALE	MALE	Total
FY19	11985	20860	32845	4127	9827	13954	34%	47%	42%
FY20	15332	26567	41899	5570	12974	18544	36%	49%	44%
FY21	20440	34455	54895	7340	15717	23057	36%	46%	42%
FY22	30781	49231	80012	9410	19448	28858	31%	40%	36%
FY23	38772	59978	98750	12279	24241	36520	32%	40%	37%
Total	117310	191091	308401	38726	82207	120933	33%	43%	39%

Table 10 shows the total number of policies with dependent child of Age 25 and at least one claim paid since inception.

Table 10: Number of Policies With At Least 1 Claim Paid Since Inception

FY	FEMALE	MALE	Total	FEMALE	MALE	Total	FEMALE	MALE	Total
FY19	7928	14246	22174	3041	7501	10542	38%	53%	48%
FY20	9990	17708	27698	4004	9644	13648	40%	54%	49%
FY21	12655	21793	34448	5069	11156	16225	40%	51%	47%
FY22	17183	27553	44736	6177	12861	19038	36%	47%	43%
FY23	20189	31882	52071	7251	14924	22175	36%	47%	43%
Total	67945	113182	181127	25542	56086	81628	38%	50%	45%

Table 11 represents the total number of policies with dependent child of Age 25 and no claim paid by the insurer since inception. These tables also highlight the renewal rate of these policies with more than one new policy.

Table 11: Number of Policies Without any Claim Paid Since Inception

FY	FEMALE	MALE	Total	FEMALE	MALE	Total	FEMALE	MALE	Total
FY19	4057	6614	10671	1086	2326	3412	27%	35%	32%
FY20	5342	8859	14201	1566	3330	4896	29%	38%	34%
FY21	7785	12662	20447	2271	4561	6832	29%	36%	33%
FY22	13598	21678	35276	3233	6587	9820	24%	30%	28%
FY23	18583	28096	46679	5028	9317	14345	27%	33%	31%
Grand	49365	77909	127274	13184	26121	39305	27%	34%	31%

The data from the above two tables (10 & 11) clearly indicate that policies with claims have higher conversion rates compared to those without claims, and the number of policies held by male customers is higher than those held by female customers. Moreover, renewal of these policies accompanied by signing up for another policy is observed more frequently among male customers than female customers. Overall, a combined conversion rate of approximately 40%-45% has been observed in the above cohorts. When analyzing renewal rates for policies with claims, female policyholders' dependents show a conversion rate of 38%, whereas male policyholders' dependents show a conversion rate of 50%.

To sum up data from tables 9,11 & 11 for a period FY 19-FY 23,Retention of those policies where there is an insured dependent of 25years supposed to take a separate policy, retention rate is 39%.However where there is an observant claim this retention rate is 45% and where is no claim the retention rate is 31%.This is a clear indication that family tree is stronger in those policies where there is an event of claim.

To further analyze the impact of claim history on policyholder behavior, the following section presents key data insights, including number of policies without claim conditions, policies with at least one claim paid since inception, and those without any claims paid since inception and also the analysis of results for RQ1 to RQ3

Results explained:

Figure 8 mentions the Decision tree matrix of 2018 as the base year of policies for analysis without portability i.e., customers who are new to Insurance with 60:40 sampling distribution.

RQ1-Modelling: Decision Tree of FY18 Fresh Policies across vintage(without port)

Data distribution for modelling:

RENEWAL	POL COUNT	% DISTRIBUTION
1	589560	63.11%
0	344612	36.89%
TOTAL	934172	100.00%

Methodology:

- We have tried multiple machine learning models and XGBoost classifier performed well. Multiple over-sampling and under-sampling pattern were tested and maximum accuracy of 69.33% was achieved on 60-40 sampling distribution. We have obtained the confusion matrix for test data as below:

ACTUAL	PREDICTED		
	Class	NO	YES
	NO	TN	FP
	YES	FN	TP

Actual	Predicted		
	Class	No	Yes
	No	59293	54429
	Yes	41166	153389

Precision-recall trade off achieved on 0.5 probability threshold. Precision and recall of class-1 for the model is 0.74 and 0.79 respectively.

	precision	recall	f1-score	support
0	0.59	0.52	0.55	113722
1	0.74	0.79	0.76	194555
accuracy			0.69	308277
macro avg	0.66	0.65	0.66	308277
weighted avg	0.68	0.69	0.69	308277

Figure 8 Decision Tree of Fy 18 Fresh Policies Across Vintage (Without Port) 60:40 sampling.

Decision Tree Model for FY18 Fresh Policies Across Vintage (Without Portability)-explained.

1. Data Distribution for Modelling-The dataset used for modelling consists of policies categorized based on renewal status. The distribution of policies is as follows:

Renewal Status	Policy Count	% Distribution
Renewed (1)	589,560	63.11%
Not Renewed (0)	344,612	36.89%
Total	934,172	100.00%

2. Methodology

A Decision Tree model was employed to predict policy renewals. The model underwent multiple rounds of training and validation using the XGBoost classifier, which demonstrated strong predictive capability.

To optimize performance, over-sampling and under-sampling techniques were implemented, with the best model performance achieved using a 60-40 sampling distribution. The highest recorded accuracy for this configuration was 69.33%.

3. Confusion Matrix for Test Data

The confusion matrix below represents the model's classification performance on test data:

Actual / Predicted	Predicted: No	Predicted: Yes
Actual: No (TN + FP)	59,293	54,429

Actual: Yes (FN + TP)	41,166	153,389

- True Negatives (TN): 59,293 False Positives (FP): 54,429
- False Negatives (FN): 41,166 True Positives (TP): 153,389

4. Model Performance Metrics

The model's effectiveness was evaluated using Precision, Recall, and F1-score for both classes.

Metric	Class 0 (Not Renewed)	Class 1 (Renewed)
Precision	0.59	0.74
Recall	0.52	0.79
F1-Score	0.55	0.76
Support (Test Samples)	113,722	194,555

Overall Model Performance

Metric	Score
Accuracy	0.69
Macro Average F1-Score	0.66
Weighted Average F1-Score	0.69

Conclusion

The Decision Tree model with XGBoost demonstrated a trade-off between precision and recall at a 0.5 probability threshold. The model exhibited higher precision (0.74) and recall (0.79) for Class-

1 (Renewed Policies), which is critical for predicting customer retention. The overall accuracy of 69% suggests that the model performs well in identifying policy renewals.

Figure 9 mentions the Decision tree matrix of 2018 as the base year of policies for analysis without portability i.e., customers who are new to Insurance with 50:50 sampling distribution.

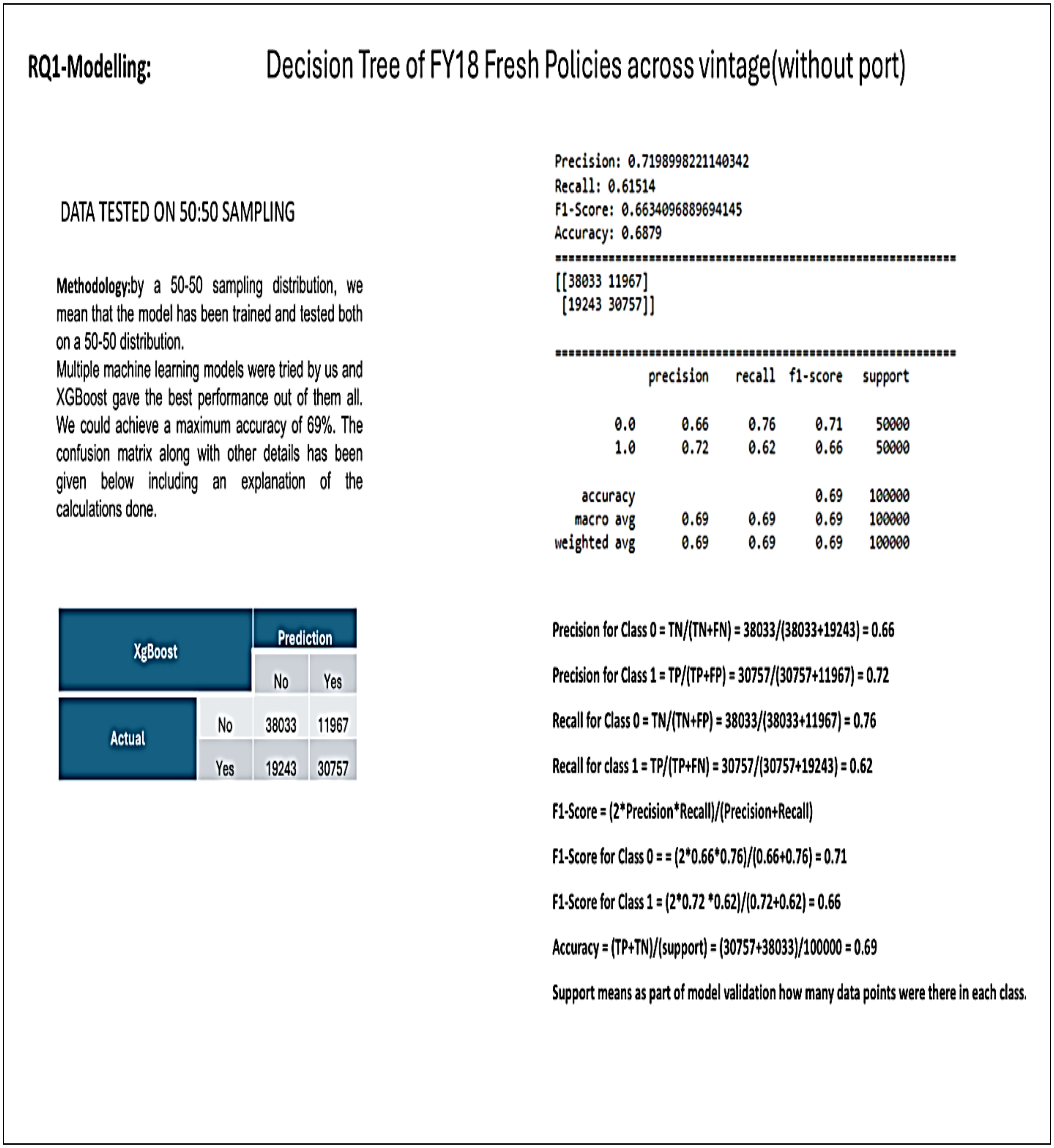

Figure 9 Decision Tree of Fy 18 Fresh Policies Across Vintage (Without Port) 50:50 sampling.

Figure 10 mentions the Decision tree matrix of 2018 as a base year of policies for analysis without portability i.e., customers who are new to Insurance with 50:50 sampling distribution with confirmation of best results.

RQ1-Modelling: Decision Tree of FY18 Fresh Policies across vintage(without port)

Data distribution for modelling ON 50:50 SAMPLING FOR MORE ACCURACY

Methodology: by a 50-50 sampling distribution, we mean that the model has been trained and tested both on a 50-50 distribution.
Multiple machine learning models were tried by us and XG Boost gave the best performance out of them all. We could achieve a maximum accuracy of 62%. The confusion matrix along with other details has been given below including an explanation of the calculations done.:

XgBoost		Prediction	
		No	Yes
Actual	No	6028	3972
	Yes	3613	6387

Precision: 0.616565305531422
Recall: 0.6387
F1-Score: 0.6274374969301046
Accuracy: 0.62075
==
[[6028 3972]
 [3613 6387]]
==

	precision	recall	f1-score	support
0	0.63	0.6	0.61	10000
1	0.62	0.64	0.63	10000
accuracy			0.62	20000
macro avg	0.62	0.62	0.62	20000
weighted avg	0.62	0.62	0.62	20000

Precision for Class 0 = TN/(TN+FN) = 6028/(6028+3613) = 0.63

Precision for Class 1 = TP/(TP+FP) = 6387/(6387+3972) = 0.62

Recall for Class 0 = TN/(TN+FP) = 6028/(6028+3972) = 0.60

Recall for class 1 = TP/(TP+FN) = 6387/(6387+3613) = 0.64

F1-Score = (2*Precision*Recall)/(Precision + Recall)

F1-Score for Class 0 = = (2*0.63*0.60)/(0.63+0.60) = 0.61

F1-Score for Class 1 = (2*0.62 *0.64)/(0.62+0.64) = 0.63

Accuracy = (TP+TN)/(support) = (6387+6028)/20000 = 0.62

Support means as part of model validation how many data points were there in each class.

Figure 10 Decision Tree of Fy 18 Fresh Policies Across Vintage (Without Port) 50:50 sampling.

Decision Tree Model for FY18 Fresh Policies Across Vintage (Without Portability)-Explained

Data Distribution for Modelling-The dataset used for modelling consists of policies categorized based on renewal status. The distribution of policies is as follows:

Renewal Status	Policy Count	% Distribution
Renewed (1)	589,560	63.11%
Not Renewed (0)	344,612	36.89%
Total	934,172	100.00%

2. Methodology

A Decision Tree model was employed to predict policy renewals. The model underwent multiple rounds of training and validation using the XGBoost classifier, which demonstrated strong predictive capability.

To optimize performance, over-sampling and under-sampling techniques were implemented, with the best model performance achieved using a 50-50 sampling distribution, improving accuracy to 62%.

3. Confusion Matrix for Test Data

The confusion matrix below represents the model's classification performance on test data:

Actual / Predicted	Predicted: No	Predicted: Yes
Actual: No (TN + FP)	6,028	3,972
Actual: Yes (FN + TP)	3,613	6,387

- True Negatives (TN): 6,028 False Positives (FP): 3,972
- False Negatives (FN): 3,613 True Positives (TP): 6,387

4. Model Performance Metrics

The model's effectiveness was evaluated using Precision, Recall, and F1-score for both classes.

Metric	Class 0 (Not Renewed)	Class 1 (Renewed)
Precision	0.63	0.62
Recall	0.63	0.64
F1-Score	0.61	0.63
Support (Test Samples)	10,000	20,000

Overall Model Performance

Metric	Score
Accuracy	0.62
Macro Average F1-Score	0.62
Weighted Average F1-Score	0.62

Model Conclusion

The Decision Tree model with XGBoost demonstrated a trade-off between precision and recall at a 0.5 probability threshold. The model exhibited higher recall (0.64) for Class-1 (Renewed Policies), which is critical for predicting customer retention. The overall accuracy of 62% suggests that the model performs adequately in identifying policy renewals.

RQ1-Modelling- Explained

The base data starting with the year 2018 has a Matrix of 79% of the insured having PED and 21% not having a PED and we have measured retention against this sample. However, the sampling of for analysis was done with 60-40 (figure 8) distribution. The same was done to give all observations a fair chance of being predicted equally when no information is available to predict success/failure.TP stands for True Positive and defined as an outcome where the model correctly predicts the positive class. Similarly, TN, a true negative is an outcome where the model correctly predicts the negative class. Then the data was tested with 50-50 sampling distribution for more robustness (figure 9). This was further tested for more accuracy on 50-50 sampling and the best results were evident by the results obtained as reflected in figure 10.

Precision measures how good our model is when the prediction is positive. How often did the model predicted (Table12) the event to be positive and it turned out to be true? Assume the predicted positive is 60 and the true positive is 50. It would be the ratio of True Positive to cases that were predicted positive. Therefore, the precision is 50/60. Accuracy is how often the model predicted correctly. The ratio of the true cases to all the cases. Recall measures how good our model is at correctly predicting positive classes.

Table 12: Precision testing

PRECISION TESTING	
Precision for Class 0 = TN/(TN+FN) = 92793/ (92793+13120) = 0.88	Precision for Class 1 = TP/(TP+FP) = 26383/ (26383+37635) = 0.41
Recall for Class 0 = TN/(TN+FP) = 92793/ (92793+37635) = 0.71	Recall for class 1 = TP/(TP+FN) = 26383/ (26383+13120) = 0.67

F1-Score = (2*Precision*Recall)/ (Precision + Recall)	
F1-Score for Class 0 = = (2*0.88*0.71)/ (0.88+0.71) = 0.79	F1-Score for Class 1 = (2*0.41*0.67)/ (0.41+0.67) = 0.51

We cannot try to maximize both precision and recall because there is a trade-off between them.

Table 13 mentions feature importance of all features which have been calculated using XGBoost feature importance. Since inception reported claim through medical has come out as the most important feature of the model.

Table 13: Top ten variables are listed below in order of significance.

	Features	Feature Importance	Remarks
1	MEDICAL_REPORTED_COUNT_INC	24.01%	Medical management claims
2	CLAIMED_MEMBERS	19.74%	Number of claimants
3	SURGICAL_REPORTED_COUNT_INC	14.77%	Surgery claims
4	VINTAGE	9.01%	numbers of years of policy existence
5	TOTAL_REJECTED_CNT_1Y	5.54%	Claims rejected in first year
6	POLICY_TYPE	2.89%	Whether floater or individual
7	PORTAL_NAME	1.98%	How was the policy sourced? Offline or online
8	CHNL_TYPE_STATUS_COMPOSITE AGENTS	1.79%	Agent who sourced the policy composite or IC38
9	CASHLESS_REPORTED_COUNT_INC	1.58%	Nature of claim. Cashless or reimbursement
10	PROD_OTHERS	1.13%	What is the product in which the customer is ensured

RQ2 – Does Induced Claim Impact Renewal Retention?

RQ2-Modelling: Induced Claim impact on retention

Data taken for modelling: from FY-19 to FY-23

RENEWAL DUE TO PHC CLAIMS	POLICY COUNT	% DISTRIBUTION
1	257272	79.85%
0	64907	20.15%
TOTAL	322179	100.00%

XGBoost classifier performed well. Multiple over-sampling and under-sampling methods were tested and maximum accuracy of 71% was achieved on 60-40 sampling distribution. Confusion matrix for test data as below:

		PREDICTED	
	Class	NO	YES
ACTUAL	NO	TN	FP
	YES	FN	TP

	Predicted		
Actual	Class	No	Yes
	No	4310	8671
	Yes	10114	41341

Precision-recall trade off achieved on 0.55 probability threshold. Precision and recall of class-1 for the model is 0.83 and 0.81

```
              precision    recall  f1-score   support

           0       0.30      0.33      0.31     12981
           1       0.83      0.80      0.81     51455

    accuracy                           0.71     64436
   macro avg       0.56      0.57      0.56     64436
weighted avg       0.72      0.71      0.71     64436
```

Figure 11 Modelling: Induced Claim impact on retention.

Induced Claim Impact on Retention-Data Distribution for Modelling

The dataset used for modelling consists of policies categorized based on whether claims were induced due to PHC. The distribution of policies is as follows:

Renewal Due to PHC Claims	Policy Count	% Distribution
1 (Renewed)	257,272	79.85%
0 (Not Renewed)	64,907	20.15%
Total	322,179	100.00%

2 Methodology

The XGBoost classifier was used for predicting policy renewals. The model was trained and validated with multiple over-sampling and under-sampling techniques to optimize performance. The best performance was obtained using a 60-40 sampling distribution, achieving a maximum accuracy of 71%.

3. Confusion Matrix for Test Data

The confusion matrix below represents the model's classification performance on test data:

Actual / Predicted	Predicted: No	Predicted: Yes
Actual: No (TN + FP)	4,310	8,671
Actual: Yes (FN + TP)	10,114	41,341

- True Negatives (TN): 4,310 False Positives (FP): 8,671
- False Negatives (FN): 10,114 True Positives (TP): 41,341

4. Model Performance Metrics

The model's effectiveness was evaluated using Precision, Recall, and F1-score for both classes.

Metric	Class 0 (Not Renewed)	Class 1 (Renewed)
Precision	0.30	0.83

Metric	Class 0 (Not Renewed)	Class 1 (Renewed)
Recall	0.33	0.80
F1-Score	0.31	0.81
Support (Test Samples)	12,981	51,455

Overall Model Performance

Metric	Score
Accuracy	0.71
Macro Average F1-Score	0.56
Weighted Average F1-Score	0.71

5. Conclusion

The Decision Tree model with XGBoost demonstrated a trade-off between precision and recall at a 0.55 probability threshold. The model exhibited higher precision (0.83) and recall (0.80) for Class-1 (Renewed Policies), which is essential for retention analysis. The overall accuracy of 71% suggests that the model performs well in identifying policies renewed due to PHC claims.

RQ2-Modelling: Explained

The base data starting with the year 2019-23 (figure 11) has a Matrix of 80% retention being stronger where PHC has been done and 20% where retention has not happened. However, the sampling of for analysis was done with 60-40 distribution. The same was done to give all observations a fair chance of being predicted equally when no information is available to predict the success/failure TP stands for True Positive and defined as an outcome where the model correctly predicts the positive class. Similarly, TN, a true negative is an outcome where the model correctly predicts the negative class.

Precision (Table 14) measures how good our model is when the prediction is positive. How often did the model predict the event to be positive and it turned out to be true? It would be the ratio of True Positive to cases that were predicted positive. Accuracy is how often the model predicted correctly. The ratio of the true cases to all the cases. Recall measures how good our model is at correctly predicting positive classes.

Table 14: Precision testing

PRECISION TESTING	
Precision for Class 0 = TN/(TN+FN) = 4310/ (4310+10114) = 0.30	Precision for Class 1 = TP/(TP+FP) = 41341/ (41341+8671) = 0.83
Recall for Class 0 = TN/(TN+FP) = 4310/ (4310+8671) = 0.33	Recall for class 1 = TP/(TP+FN) = 41341/ (41341+10114) = 0.80

F1-Score = (2*Precision*Recall)/ (Precision + Recall)	
F1-Score for Class 0 = = (2*0.30*0.33)/ (0.30+0.33) = 0.31	F1-Score for Class 1 = (2*0.83*0.80)/ (0.83+0.80) = 0.81

We cannot try to maximize both precision and recall because there is a trade-off between them Importance of all features has been calculated using XGBoost feature importance. Total reported claim count in past 1 year has come out as the most important feature of the model. model. The top ten variables (Table 15) are listed below in order of significance.

Table 15: Top ten variables are listed below in order of significance.

	Features	Feature Importance	Remarks
1	PROD_SURPLUS-FLOATER	19.10%	What Product customer has chosen
2	PROD_OTHERS	14.29%	What Product customer has chosen
3	PROD_FHO	6.61%	What Product customer has chosen
4	CHNL_TYPE_STATUS_OTHERS	5.02%	How was the policy sourced? Offline or online
5	PORTAL_NAME	4.39%	What is the channel which sourced the policy
6	RISK_COUNT	4.28%	How many lives are covered in the policy
7	BDREN_CNT	2.39%	How many years the policy has run with company
8	CHNL_TYPE_STATUS_Office Direct	2.35%	What is the channel which sourced the policy
9	CHNL_TYPE_STATUS_Sales Direct	2.06%	What is the channel which sourced the policy
10	CHNL_TYPE_STATUS_Tele Marketer	1.97%	What is the channel which sourced the policy

RQ3-Creation of Family tree

Figures 12 looks at the influence of claim on dependent buying a separate policy based on data from FY-19 to FY 23

RQ3-Modelling: **Creation Of Family Tree**

Data taken for modelling: FY-19 to FY-23

POLICY SPLIT	POLICY COUNT	% DISTRIBUTION
1	119705	38.81%
0	188701	61.19%
TOTAL	308406	100.00%

XG Boost classifier performed well. Multiple over-sampling and under-sampling pattern were tested and maximum accuracy of 70% was achieved on 50-50 sampling distribution. Confusion matrix for test data as below:

		PREDICTED	
ACTUAL	Class	NO	YES
	NO	TN	FP
	YES	FN	TP

Actual	PREDICTED		
	Class	No	Yes
	No	92793	37635
	Yes	13120	26383

Precision-recall trade off achieved on 0.55 after trying multiple combinations of probability threshold

	precision	recall	f1-score	support
0.0	0.88	0.71	0.79	130428
1.0	0.41	0.67	0.51	39503
accuracy			0.70	169931
macro avg	0.65	0.69	0.65	169931
weighted avg	0.77	0.71	0.73	169931

Figure 12 Modelling: Creation of Family Tree

Creation of Family Tree - Modelling FY19 to FY23

1. Data Distribution for Modelling-The dataset used for modelling consists of policies categorized based on policy split. The distribution of policies is as follows:

Policy Split	Policy Count	% Distribution
1	119,705	38.81%
0	188,701	61.19%
Total	308,406	100.00%

2. Methodology

The XGBoost classifier was used for predicting policy outcomes. The model was trained and validated with multiple over-sampling and under-sampling techniques to optimize performance. The best performance was obtained using a 50-50 sampling distribution, achieving a maximum accuracy of 70%.

3. Confusion Matrix for Test Data

The confusion matrix below represents the model's classification performance on test data:

Actual / Predicted	Predicted: No	Predicted: Yes
Actual: No (TN + FP)	92,793	37,635
Actual: Yes (FN + TP)	13,120	26,383

- True Negatives (TN): 92,793 False Positives (FP): 37,635
- False Negatives (FN): 13,120 True Positives (TP): 26,383

4. Model Performance Metrics

The model's effectiveness was evaluated using Precision, Recall, and F1-score for both classes.

Metric	Class 0 (Not Renewed)	Class 1 (Renewed)
Precision	0.88	0.41
Recall	0.71	0.67
F1-Score	0.79	0.51
Support (Test Samples)	130,428	39,503

Overall Model Performance

Metric	Score
Accuracy	0.70
Macro Average F1-Score	0.65
Weighted Average F1-Score	0.73

5. Conclusion

The Decision Tree model with XGBoost demonstrated a trade-off between precision and recall at a 0.55 probability threshold. The model exhibited higher precision (0.88) for Class-0 (non-renewed) and recall (0.67) for Class-1 (Renewed Policies). The overall accuracy of 70% suggests that the model performs well in policy classification.

RQ3-(figure 12) Modelling: Explained Feature importance of all features has been calculated using XGBoost feature importance. Policy that belongs to Surplus-floater product has come out as the most important feature of the model.

The base data starting with the year 2019-23 has a Matrix of 61% of insured taking dependent policy thereby starting a family tree after experiencing claim being stronger. However, the sampling of for analysis was done with 50-50 distribution. The same was done to give all observations a fair chance of being predicted equally when no information is available to predict success/failure.TP stands for True Positive and defined as an outcome where the model correctly predicts the positive class. Similarly, TN, a true negative is an outcome where the model correctly predicts the negative class.

Precision measures (Table 16) how good our model is when the prediction is positive. How often did the model predicted the event to be positive and it turned out to be true? It would be the ratio of True Positive to cases that were predicted positive. Accuracy is how often the model predicted correctly. The ratio of the true cases to all the cases. Recall measures how good our model is at correctly predicting positive classes.

Table 16: Precision testing

PRECISION TESTING	
Precision for Class 0 = TN/(TN+FN) = 6028/ (6028+3613) = 0.63	Precision for Class 1 = TP/(TP+FP) = 6387/ (6387+3972) = 0.62
Recall for Class 0 = TN/(TN+FP) = 6028/ (6028+3972) = 0.60	Recall for class 1 = TP/(TP+FN) = 6387/ (6387+3613) = 0.64

F1-Score = (2*Precision*Recall)/ (Precision + Recall)	
F1-Score for Class 0 = = (2*0.63*0.60)/ (0.63+0.60) = 0.61	F1-Score for Class 1 = (2*0.62 *0.64)/ (0.62+0.64) = 0.63

We cannot try to maximize both precision and recall because there is a trade-off between them.

The top ten variable as mentioned in Table 17 are influencing these results.

Table 17: Top ten variables are listed below in order of significance.

	Features	Feature Importance	Remarks
1	PROD_SURPLUS-FLOATER	19.10%	What Product customer has chosen
2	PROD_OTHERS	14.29%	What Product customer has chosen
3	PROD_FHO	6.61%	What Product customer has chosen
4	PORTAL_NAME	4.65%	What is the channel which sourced the policy
5	RISK_COUNT	4.25%	How many people are covered in the policy
6	CHNL_TYPE_STATUS_OTHERS	3.60%	What is the channel which sourced the policy
7	CHNL_TYPE_STATUS_Tele Marketer	3.56%	What is the channel which sourced the policy
8	CHNL_TYPE_STATUS_Sales Direct	2.65%	What is the channel which sourced the policy
9	BDREN_CNT	2.26%	How many years the policy has run with company
10	PREMIUM	2.01%	How many people are covered in the policy

RQ3-Modelling: Customer lifetime value-new finding and GAP in existing literature

Customer Lifetime Value (CLV) is a fundamental metric in strategic marketing and customer relationship management, serving as a quantitative measure of the total financial contribution a customer is expected to generate throughout their relationship with a business. It enables organizations to assess the long-term economic value of customer retention and engagement, facilitating data-driven decision-making in marketing resource allocation, pricing strategies, and service personalization. The core premise of CLV lies in its predictive capability, allowing firms to estimate future revenue streams derived from existing customers, thereby optimizing marketing expenditures and ensuring a more sustainable growth trajectory. One of the primary justifications for calculating CLV is its strong correlation with customer retention, as research indicates that the probability of selling to an existing customer (60%–70%) far exceeds the probability of converting a new prospect (5%–20%), underscoring the financial advantage of prioritizing retention over acquisition strategies. By promoting greater customer interaction, boosting recurring business, and lowering attrition rates, companies that successfully use CLV-driven insights can greatly increase profitability.

CLV Computation can be done with the application of the different methodologies, however all these methodologies have some kind of intricacy and accuracy. These methodologies provide estimate across customer segments for assessment of the CLV at a customer-specific level. However, conventionally, CLV as individual level is defined as the net present value of all the cash flows for future which is attributed to maintain customer relationship in specific manner which is adjustable to cost incur in the acquisition, servicing and retention. This strategy guarantees that companies correctly identify high-value clients, allocate resources optimally, and create focused marketing campaigns that maximize profitability and long-term engagement.

Additionally, by incorporating CLV into strategic decision-making frameworks, businesses can improve personalized engagement efforts, optimize pricing models, and more effectively allocate marketing budgets, guaranteeing that high-value clients receive unique offerings catered to their requirements and behavioral patterns. Organizations that systematically use CLV as a guiding metric are better positioned to foster sustainable growth, strengthen customer loyalty, and achieve a higher return on marketing investment in today's competitive markets, where customer-centricity and data-driven personalization dictate business success. Businesses can proactively anticipate customer demands, improve service experiences, and put loyalty-driven retention plans into place that strengthen brand equity and customer lifetime profitability by coordinating CLV with more general company objectives.

$$CLV_i = \sum_{t=1}^{N} \frac{(p_{i,t} - c_{i,t}) pr_{i,t}}{(1 + i)^t} - AC_i$$

Pi,t = Price paid by the customer at time t,

Ci,t = Cost of serving the customer at time t,

i = Discount rate,

PRi,t = Probability rate of the customer being active at time t,

ACi = Acquisition cost of the customer.

CLV is not only used as a calculation framework, however, used in the form of a strategic framework for CRM optimization, judicious marketing investment and ensuring business sustainability in the long-term (See Figure 11). After the computation of CLV, the metrics can be used by businesses for decision making process driven through data in multiple strategic functions such as enhancing retention rate, optimization of acquisition, segmentation of customers, improving the rate of forecasting and identify highly valued customers. CLV driven customer segmentation facilitates businesses to have efficient resource allocation and engaging high-valued customers through personalized engagement and via premium service offerings for improvement in customer loyalty and winning business profitability. The main focus of the convention CLV models were on the customer profitability and comprised to consider family dynamics in broader context for determining the customer relationship economic value. With the application of the conventional business valuation methods, the number of individuals customers was measured but the number of lives influence by individual customers were not measures. These methods are used to overlook the fact that with satisfaction of the entire family unit the rate of customer retention is enhanced, and businesses can drive organic growth via using referrals of the family and adoption of multiple policies. The inclusion of the entire family in the CLV calculation enables the firms to gain CRM value in holistic manner when a policy holder gets satisfactory services, it results into referring other family members and via winning their trust and as a result of this customer retention and policy conversion rate is enhanced. Hence the integration of CFV and CLV as a combined approach proves a comprehensive measure for ensuring long-term business profitability. This approach affirms that business can have customer retention and enhancement of revenue rate via including entire family network and it helps the business to lead market expansion in the increasing competitive landscape of the insurance sector. This is depicted in Figure 13.

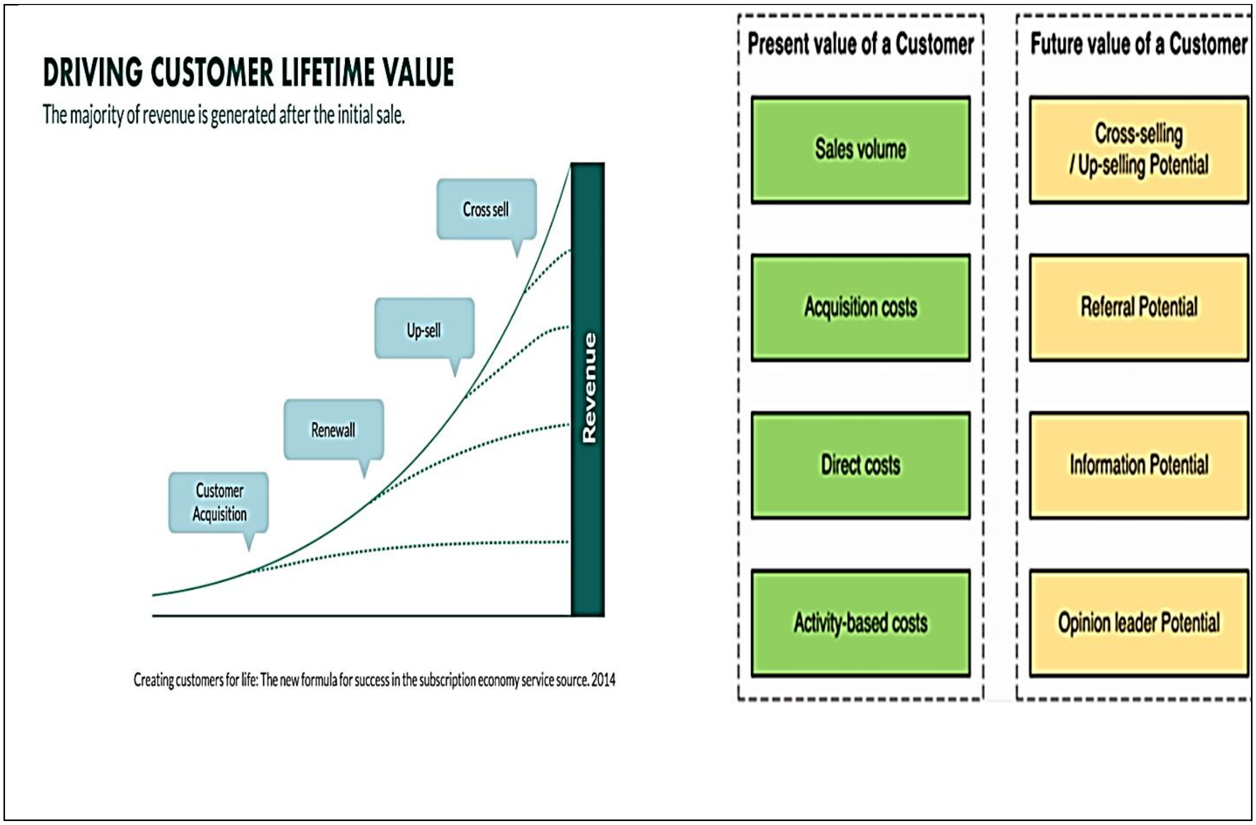

Figure 13 Driving CLV

Customer Lifetime Value (CLV) falls in direct correlation with a falling renewal rate and worsening customer retention, which has both short-term and long-term monetary consequences. Loss of both current and prospective customers from the same home is possible when policyholders are unhappy with their insurer, which raises the risk of policy lapse and competitor-driven customer attrition.

The parent or main policyholder's disengagement results in a multiplied loss beyond the individual policy since they frequently serve as the family's opinion leader, impacting the insurance choices of dependents and extended family members. This highlights the larger strategic point that keeping customers isn't just about keeping in touch with them; it's also crucial for retaining market share across generations. Because unhappy consumers are more likely to transfer insurers and may even deter prospective new customers from interacting with the provider via poor word of mouth, a failure to retain current customers allows rivals to expand their market share. The exponential financial impact of sustained policyholder engagement is illustrated by empirical evidence from Bain & Co. and Harvard Business School (2000), which shows that even a small increase of 5% in customer retention can drive a growth in profitability of 25% to 95%. This competitive dynamic is in line with these findings. The financial advantages of retention-focused tactics compound over time, and this is true not just in terms of direct revenue implications but also in terms of referral-based acquisition, as a happy customer base naturally creates new business at minimum acquisition cost.

Consequently, it is critical to keep customers happy. According to Gartner, 75 percent of companies can prove a correlation between customer lifetime value (CLV) and customer happiness. This proves that companies who put money into CX strategies for the long haul end up with much better revenue results. With few ways to stand out in the increasingly standardized insurance industry, insurers are finding that providing exceptional customer experience is the best way to attract and retain customers. The insurance business is seeing an 18% difference between consumer expectations and the actual service delivery, according to a PWC analysis on the future of customer experience (CX). This mismatch is widening, which is making policyholders even less satisfied and reducing renewal rates. Also, according to a study by the Institute of Customer Service, insurance companies' customer satisfaction ratings have been falling, which means they really need to rethink their engagement tactics to meet their customers' changing expectations.

As a key performance indicator (KPI) for measuring the efficacy of customer experience initiatives, CLV demonstrates that companies who focus on loyalty-driven engagement bring disproportionate long-term value to their organization. Insurers who undertake CX-focused retention strategies and succeed are positioned for greater valuations and perhaps re-ratings in the market, according to industry insights from Phipps, since increased customer loyalty immediately correlates to enhanced profitability. Insurers, in light of the strategic, financial, and competitive ramifications of retention-centric business models, would do well to see client retention as more than just an operational objective; it is, rather, a critical component of long-term growth, profitability, and improved brand equity in the insurance industry's cutthroat environment. Following this, we'll go over some of the management takeaways from these results, which should help insurers improve client retention and engagement in the long run.

Discussion/Managerial Implications

According to the results, there is a strong correlation between the number of insurance claims and the percentage of consumers who renew their health insurance. Managers in health insurance policies should think about ways to improve the claim process in order to boost renewal rates and consumer loyalty. Improving customer satisfaction and loyalty via focused communication methods after claim occurrences might impact their choice to renew policies with the insurer. One way to improve retention rates and cultivate long-term relationships with customers is to track claim trends and use that data to create targeted retention initiatives.

Higher retention rates among health insurance clients are associated with PHC messaging. The insurance service providers can make the customers aware with the advantages of PHC such as detection and prevention of health conditions at early stage and hence motivate them to use PHC. This boosts the perceived value of the insurance coverage and encourages proactive healthcare. Although the company's financial management may see PHC communication as a cost, it really has the ability to create long-term relationships with customers and bring in prospective revenues for the insurance provider. In order to educate and incentivize consumers, this research suggests that health insurance firms should prioritize PHC integration as a key service offering and use focused communication tactics. Additionally, the report suggests that managers think about when it's best to notify consumers about PHC when the insurance is about to expire. This study approach can be applied by the insurers in their business model for examining the impact of PHC on the claim reduction and customer retention. With this approach, future research studies can be conducted in an organized manner for examining the relationship between claims and probability of purchasing insurance policy from same insurer by the other members of the same family. The results of this study may help insurance firms better understand their customers and create products that will appeal to them and their families. Insurance firms could increase customer retention rates via better claims management and broaden their market reach by capitalizing on familial ties to advocate for new policies if they highlighted the positive impact of claims advocacy on Family CLV and integrated the study's findings into operational models. Building customer loyalty and happiness throughout generations within a home is a key component of sustained company success, which may be achieved via this strategic approach.

Insurance firms stand to gain from this research, but policyholders stand to gain as well, since they will have a better understanding of the worth of their policies and be happier overall with the coverage they have. As the need for primary health care (PHC) services rises, healthcare institutions and providers may approach health insurers about forming partnerships and collaborations. The results of this research have many applications for policymakers. One possible application of the study's findings is to influence policymaking in a way that encourages and supports preventative healthcare practices, such as PHC health insurers include PHC in their service offers. This might ultimately enhance the general population health. Second, lawmakers may be better guided in the formulation of cost-effective healthcare legislation if they have a firm grasp of how PHC affects the reduction of healthcare costs via early identification and prevention. Last but not least, regarding insurance regulation and consumer protection, lawmakers might use the results to guarantee openness in PHC coverage, making sure that policyholders know all the advantages they have access to.

In a complex and ever-changing economic environment, health insurance companies face mounting financial pressures caused by medical inflation outpacing general inflation. As a result, these companies must periodically adjust premiums to stay solvent, guarantee claims liquidity, and comply with regulatory capital requirements (Deloitte, 2021). In the health insurance industry, consumers are more likely to perceive premium hikes as exploitative or arbitrary, which can lead to higher lapse rates, less brand loyalty, and even migration to competitor policies with more attractive pricing structures. This is in contrast to other industries where consumers have more leeway to absorb price adjustments. Insurers are caught in an endless loop of trying to balance financial stability with customer retention imperatives as medical inflation accelerates, increasing hospitalization costs, pharmaceutical price surges, the burden of chronic diseases, and diagnostic capabilities (PwC, 2021). The capacity of an insurer to efficiently handle claims can be eroded by mounting underwriting losses in the absence of strategic premium recalibrations. Meanwhile, unregulated price hikes can cause adverse selection, in which healthier, lower-risk policyholders leave because they can't afford it, creating a concentrated group of high-risk individuals with increased claims exposure, worsening financial hardship, and putting further upward pressure on premiums (NAIC, 2020).

In light of this dynamic, insurers must devise retention strategies that actively engage customers, reinforce perceived value, and use behavioral economic insights to redirect consumer attention from short-term cost sensitivity to long-term benefits in order to overcome the psychological resistance to premium hikes. Due to decreased acquisition costs, improved cross-selling and upselling potential, and the sustained compounding effect of long-term policyholder relationships, studies show that customer retention is far more profitable than customer acquisition. In fact, research from Bain & Co. and Harvard Business School (2000) found that a mere 5% increase in retention rates can drive profitability improvements of 25% to 95%. The economic and strategic imperative of concentrating on renewal retention rather than growth strategies based solely on acquisitions is reinforced by the fact that retaining current customers not only stabilizes revenue but also strengthens an insurer's referral-based organic acquisition network. This is because happy policyholders become brand advocates, increasing adoption rates within their social circles and reducing the need for expensive lead-generation campaigns.

Premium increases are required by actuaries, but there must be engagement mechanisms to offset them so that policyholders aren't disappointed, and insurance is still worth buying for reasons other than cost. Insurers need to create segmented pricing strategies, personalized discount structures, and behavioral reinforcement mechanisms to increase customer loyalty and decrease price-related attrition risks because consumer psychology is overly sensitive to perceived fairness, transparency, and service differentiation (Schlesinger & Schulenburg, 2013).

Reduced churn and preserved actuarial balance in the risk pool are the results of a data-driven strategy for policyholder segmentation that fairly distributes premium adjustments to lower-risk, low-claim policyholders via moderated rate increases or loyalty-based incentives. The perception of the policyholder is changed from a financial obligation to a holistic health partnership that delivers tangible long-term benefits through value-added services like telemedicine, wellness programs, chronic disease management, and preventive screenings (PwC, 2021). The significance of customer involvement in reducing lapse risks is shown by empirical studies that show policyholders with better renewal rates, especially when faced with additional premium increases, when they get active and demonstrated benefits from their insurance provider. Furthermore, it is crucial to keep policyholders informed and educated about pricing adjustments. Customers are more willing to accept premium hikes when they are given clear and data-backed explanations about medical inflation trends, claims utilization patterns, and industry-wide cost drivers (McKinsey, 2022).

Research in behavioral economics supports the idea that consumers are more resistant to change when they are unsure of what to expect. As a result, proactive engagement, targeted outreach, and disclosures on regulatory compliance are crucial trust-building elements that influence the likelihood of renewal. In addition, insurers can address affordability concerns by implementing modular policy structures, tiered coverage variations, and flexible payment models. This will enable customers to adjust their insurance plans according to their budgets without cancelling their policies completely, which will reduce customers' involuntary churn and stabilize premium revenue streams (Tennyson, 2011).

Recognizing that an overemphasis on short-term fiscal austerity measures can lead to unintended consequences such as damaged customer relationships, diminished brand equity, and diminished competitive positioning, insurers face a larger structural challenge in finding a balance between cost efficiency and long-term strategic sustainability, which goes beyond immediate customer retention strategies. A major flaw in cost-cutting plans is that they don't consider the knock-on effects of less service differentiation, cancelled engagement initiatives, and damaged consumer trust. These factors lead to increased attrition and will force businesses to spend more money on reacquisition in the future.

Conservative budgetary policies may seem like a smart idea in the short term, but they may have disastrous long-term effects, such as a precipitous decline in market share that forces insurer to spend more money than they saved in the beginning to win back customers' trust.

Contrary to this, insurance companies can turn their focus on some crucial practices of digital transformation, segmenting risks via predictive analytics and service customization via AI and thereby overcome challenges of price competition and attain significant client retention level. Preventive Health Checkups (PHCs) are the most crucial examples of long-term strategic initiatives which result into decreasing the liabilities of the future claims and enhance the degree policyholder engagement but for the same purpose they require to adjust in premiums and ensuring consistent participation over dissatisfaction driven churn. It is revealed by the evidences that via providing wellness and preventive related claims, the insurance companies can secure financial rewards in the strategic claim induction. In the proactive strategy, settlement of the claims can result into client retention by reducing the occurrence of catastrophic claims, enhancement of the trust of policyholders and increment in the likelihood of the policy renewal. Insurance companies seeking for cost saving in the short-run and compromise with customer engagement in the long-term, avoid customer centric services and do not give digital experience to the consumers are restricted to maintain the same market momentum that they lost. Because dissatisfied customers are more likely to leave, insurers have to invest a lot of money in acquiring new clients, which is typically more costly than the money they save by reducing expenses.

Health insurers have three challenges: using digital, behavioral, and actuarial strategies to balance customer loyalty and financial sustainability; using proactive engagement mechanisms to increase policyholder commitment and revenue predictability; and providing unique service experiences and trust-building programs in addition to price adjustments.

For retention optimization, minimize lapse risks, and solidify market positioning within an increasingly competitive industry landscape, advanced actuarial forecasting, machine learning-driven customer segmentation, and multi-channel engagement strategies must be implemented.

Focusing only on the cost-saving approach is not good practice for the insurance companies as the customer expectations of personalization, transparency and digital accessibility are comprised with this approach. Hence, insurance companies need to implement inclusive retention strategies for maximization of CLV for keeping the policyholders engaged in the long run rather than just interacting during transactions. Companies require to build an ecosystem where trustworthy and innovative services are the keys to have strategic differentiation. Insurers who are able to maintain balance of customer-centric engagement gain multifaceted benefits namely long-term business profitability, gaining leading business position in the industry, readiness for dealing with regulatory changes and dealing with technological disturbances and having easily managed price wars. In the industry sector, for gaining expected success, adoption of loyalty driven operating model which focuses on combining the fiscal responsibility and customer relationship in sustainable manner. The insurance ecosystem is changing globally, and hence this model proves contributing to maintain business profitability, competitive advantage and retention of policy holders, instead of just considering financial prudence. The leading firms tend to maintain this balance in the finest manner. Businesses can increase their revenue rate and have good market expansion via having implementing trust-centric customer engagement models, data-driven insights and behavioral reinforcement. It becomes crucial in the insurance industry because it has a close association between consumer confidence and financial stability.

The conclusions of this research are driven and suggest other roadmaps for conducting further business investigation on other aspects related to the business world. This study was mainly purposed to examine the potential of an Indian private insurance company in dealing with insurance claims and PHC communications for the purpose of CLV and customer retention. The study undertook examining three theories related to customer retention, claims' impact and PHC messaging for covering the data from financial year 2018 to financial year 2023. In response to Hypothesis 1, it satisfactorily resulted in meeting insurance claims impacts the policy renewal inn a favorable manner. The research results back up this theory by supporting from the information gained for financial year 2022 that those policyholders who had claims met satisfactorily had improve retention rate of policy renewal in comparison to those who did not have any policy claims. Hypothesis 2 was developed for testing the impact of PHC communications on the customer retention rate.

Conclusion

Using an XGBoost Classifier, the quasi-experiment ran from FY 2022 to FY 2023 and found that retention rates go up when PHCs communicate well. The usefulness of proactive health management solutions in improving customer loyalty is shown by the rise in claims linked to PHC and the reported 7-8% gain in retention rates. Family CLV is a new notion that is introduced in Hypothesis 3 (H3). It improved Family CLV by looking at how a claim would affect policyholders' dependents who choose the same insurer. Among male policyholders in particular, the data showed that policies with claims led to increased conversion rates for dependent family members.

Our research shows that PHC communications and insurance claims have a major influence on determining customer retention tactics. In order to optimize individual and family CLV, the organization should modify its retention strategy to account for the positive association between claims and renewal rates, use PHC to increase retention, and acknowledge that claims impact family insurance choices. In order to stay ahead of the competition in the insurance industry, it is crucial to consistently invest in customer well-being and implement focused communication strategies. The results also show that these insights should be part of strategic planning.

This research supports the inclusion of Preventive Health Checkups (PHC) in the insurance management system, considering the large amounts of money the government spends on healthcare and mass insurance. Customer retention is greatly improved by PHC, according to the facts. While spending a little now on customer wellbeing may not seem like much, it will pay off in the long run via a more invested client base. In order to better prove the link between PHC claims and retention rates, future research might build on this model by doing uni- and bi-directional causality tests.

In addition to providing empirical support for these claims, this research adds to the body of knowledge on insurance retention tactics by bridging the gap between theory of consumer behavior, analytics for predictive purposes, and healthcare prevention programs. These results have far-reaching consequences for insurance policy renewals and beyond, shedding light on client engagement, strategic distinctiveness, and viability in the long run. The report highlights the need of insurers shifting their focus from one-time transactions to long-term relationships with policyholders based on mutual trust, open dialogue, and proactive value creation.

Findings support PHC inclusion into insurance management system from managerial and policy standpoints. Insurers and lawmakers should acknowledge PHC's contribution to improved client retention in light of the large sums of money the government spends on healthcare and mass insurance. Customer wellness initiatives may seem like a drain on resources at first, but they pay off in the long run through increased engagement from policyholders, less health-related uncertainty, and better retention rates. Therefore, insurance companies should focus on personalized health communication strategies that use advanced analytics to reach policyholders who will benefit the most from preventive measures. In addition, in order to create a more comprehensive and data-driven strategy for PHC implementation, insurers should investigate potential partnerships with healthcare providers, digital health platforms, and wearable tech companies.

In addition, the report stresses the need of insurers implementing a comprehensive customer retention strategy that includes proactive health management, consumer education, and conventional claims processing. Insurers should think about wellness-driven value propositions as part of their core offers, not only as supplementary services, since PHC messaging has shown to be effective. Insurance of the future will optimize risk management by improving customer experiences through the integration of interactive engagement technologies, predictive analytics, and tailored health advice. The next part expands on these developments by discussing potential avenues for additional study that could improve insurance company innovation and client retention tactics.

Future Research Directions

Even though this study has added a lot to our knowledge of retention determinants, there are still a lot of unanswered questions. To begin, the temporal dynamics of this link should be better understood with more research that uses uni- and bi-directional causality tests between PHC claims and retention rates. Second, to provide a more detailed picture of how retention techniques change over time, longitudinal research should follow customer cohorts over lengthy periods of time. Thirdly, comparison studies across markets might determine whether the retention dynamics in one insurance ecosystem are comparable to those in another, especially across developing and established economies. In the fourth place, policyholder happiness and behavioral triggers might be better understood with the use of natural language processing (NLP) approaches to consumer sentiment research. Further investigation on the behavioral aspects of PHC engagement might be conducted in the future by combining theories of decision-making and customer psychology.

It is vital for the insurance companies to develop their own health engagement models with the acknowledgement of the aspects that impact decision making tendency of policyholders to get enrollment in the PHC program. The rising rate of predictive analytics powered by AI further induced to examine the way in such machine learning models can be helpful for improvement in the customer retention tactics having new PHC suggestions for customers in customized and personalized manner. In future research studies, some additional areas can be explored such as big data, behavioral science and insurance analytics.

Final Reflections

This research implied academic theories and commercial practices to determine the relationship between insurance claims, preventative health communication and customer retention. The strategic framework suggested in this study is useful for insurance companies to increase the rate of lifetime customer value through providing explanation about the way in which claim settlement experience of the policyholders impact their retention with the same insurer and role of PHC activities in maintaining ongoing customer engagement.

The insurance sector is rapidly evolving driven through progressive technology advancements, regulatory changes and changing expectations of the customers and hence it is important for insurers to offer proactive treatment and claim settlement to ensure retention in long-run. The insurance industry in near future will have client loyalty transformation through consistent advancements in customization of the services which are data driven and customer engagement I digital health and wellness incentives which are risk-adjusted. The insurance sector is highly competitive, where insurers are required to development key strategies that are customer centric and financially sustainable. For the long-term retention of the customers, strong financial sustainability and customer lifetime value, meeting the insurance claims is the most important requisite for insurers to maintain profitability. \

Companies invest substantial resources in trying to get lower CAC(Customer Acquisition Cost) and optimize costs of overall customer management. This is one tool which can significantly benefit various sectors across industries . It can be leveraged well to enhance efficiency and cost effectiveness all across.

Claims management promotes customer involvement, trust, and long-term renewals, regardless of whether it is the result of preventative healthcare or natural medical demands. By lowering inpatient and claims costs and increasing individual health outcomes, preventive healthcare programs increase return on investment (ROI) and ensure financial stability.

By keeping costs under control, eliminating fraud, and cultivating strategic partnerships, effective claims management raises shareholder value. These partnerships also lower customer acquisition costs (CAC), boost profitability and retention, and generate steady revenue streams. Apart from monetary gains, a well-functioning insurance system improves national output, eases the strain on medical services, and improves public health. Initiatives for behavioral engagement and health literacy increase consumer empowerment, bolstering brand loyalty and guaranteeing insurers' long-term viability.

An extensive, consumer-focused insurance model that balances cost efficiency, public health needs, and financial prudence is essential. By aligning economic prosperity with social welfare, insurers can create a sustainable, high-value environment that enhances shareholder profits while improving public health outcomes.

In conclusion, as seen in Figure 14 below, the findings of this research provide a basis for future enhancements in insurance retention strategies, connecting customer welfare, risk management, and sustainable company development. By effectively integrating claims experience, PHC initiatives, and Family CLV considerations, insurers can enhance retention and cultivate deeper, more enduring relationships with policyholders and their families, thereby establishing a sustainable competitive advantage in the evolving insurance landscape.

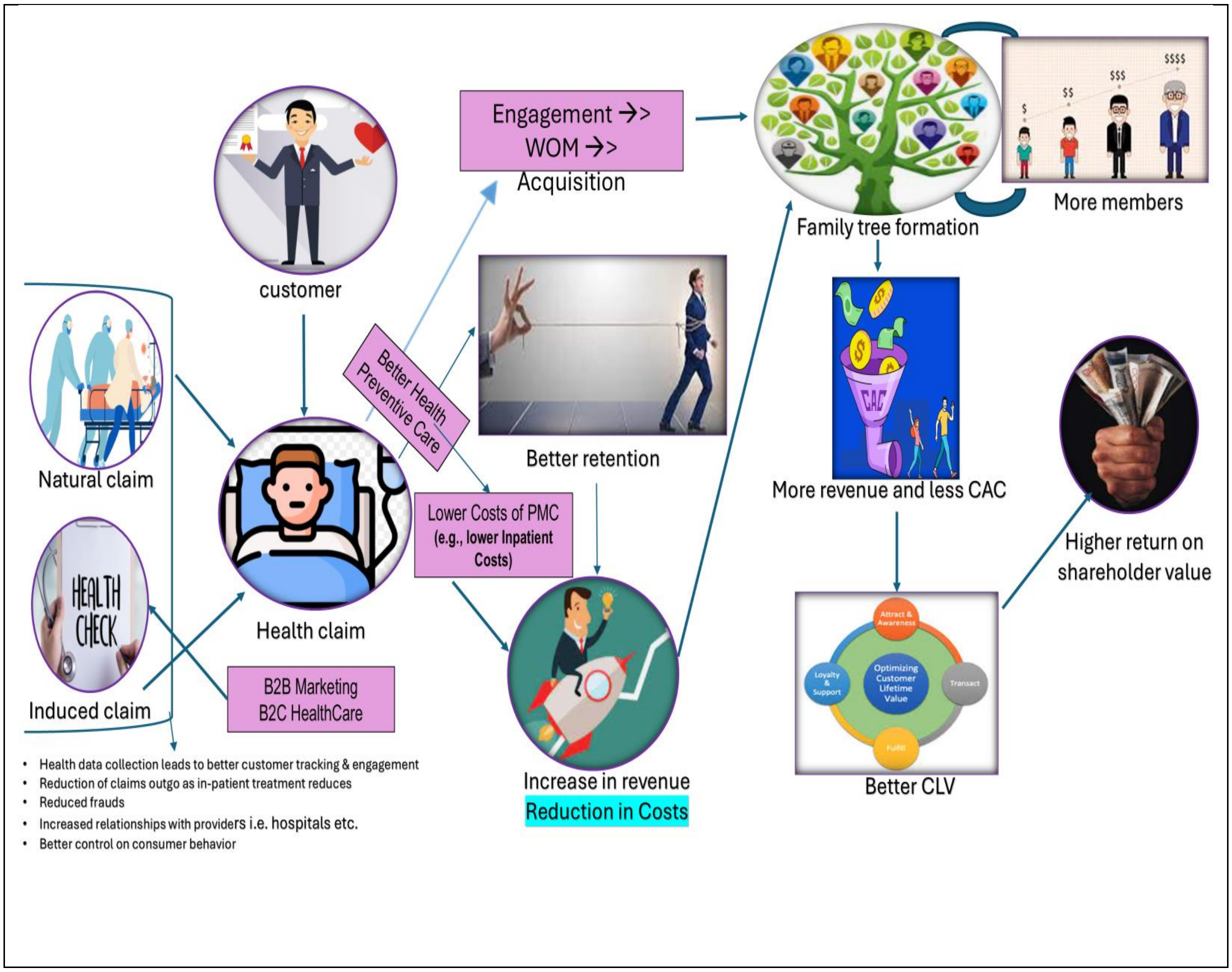

Figure 14 Impact of health insurance claim on Customer Retention & CLV

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