Babak Zarkesh

Exploring the Impact of AI-Driven Pricing on Customer Loyalty and Churn Rates in the Banking Industry

Master’s thesis in International Business and Marketing
Supervisor: Mark Pasquine
Co-supervisor: Ibrahim A. Hameed
May 2023

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Abstract

This thesis investigates the impact of AI-driven pricing strategies on customer churn in Iranian banks offering health insurance. The research problem revolves around understanding whether personalized pricing, facilitated by AI, can enhance customer loyalty and satisfaction in the Iranian financial sector. The study employs price discrimination theory and the Technology Acceptance Model as theoretical frameworks to explain the potential benefits of AI-driven pricing strategies.

The research methodology includes both quantitative and qualitative analyses, with a survey being administered to gather data on consumer perceptions and experiences with AI-driven pricing. The analysis involves a thematic exploration of the responses and frequency distributions of non-open questions.

The main findings reveal that the majority of consumers place significant importance on personalized pricing and have a favorable perception of AI-powered pricing strategies. Trust in AI-facilitated pricing emerges as a crucial factor for adoption, with most respondents experiencing an increase in trust in their banks due to AI-driven pricing. Additionally, the results highlight the need for improvement in communication to ensure AI-powered pricing mechanisms are comprehensible to all consumers.

In conclusion, the study demonstrates that AI-driven pricing strategies can be a powerful tool for reducing customer churn in Iranian financial institutions offering health insurance. By implementing these strategies, banks can increase client satisfaction and trust, address the particular challenges posed by the Iranian context, and ultimately improve customer retention rates and overall market success.

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Introduction

In recent years, the financial industry has experienced significant changes as a result of technological progress and innovations, including the integration of artificial intelligence (AI) in different areas of banking and financial services (Khan et al., 2022). The implementation of AI-powered pricing strategies in the field of health insurance, particularly in financial institutions providing such services, has been a subject of considerable interest. According to Huang and Rust (2018), the utilization of pricing strategies that are powered by artificial intelligence (AI) guarantees in enhancing customer satisfaction, trust, and loyalty, which in turn could result in decreased rates of customer churn.

The estimated customer churn in the worldwide insurance sector is approximately 25%, with certain firms encountering rates as elevated as 50% (Scriney et al., 2020). The significant rate of customer churn is a major apprehension for financial institutions due to the considerably higher cost of acquiring new customers in comparison to retaining the existing ones, as stated by Reichheld in 1996. The implementation of AI-powered pricing strategies can be essential in enhancing customer retention and loyalty within this particular framework.

The retail and e-commerce industries have been the subject of research that has established the efficacy of AI-powered pricing strategies. Personalized pricing has been found to enhance customer satisfaction and revenue, as evidenced by the findings of Chen et al. (2015). The current body of research on the effects of AI-based pricing tactics within the financial industry, specifically in banks that provide health insurance products, is limited. Furthermore, there is a lack of comprehensive research on the implementation of pricing strategies driven by artificial intelligence in nations facing challenges related to development and corruption, such as Iran.

This study aims to examine the influence of pricing strategies (personalized) powered by artificial intelligence on customer loyalty in financial institutions. The investigation will consider variables such as technology acceptance and the unique conditions of Iran's developing and corrupting environment. The study utilizes a mixed-methods methodology, incorporating both quantitative and qualitative data to comprehensively comprehend the phenomenon being examined.

The research outcomes make a valuable addition to the current knowledge on pricing strategies powered by artificial intelligence, the theory of price discrimination, and the Technology Acceptance Model (TAM). The study provides insights into the possible advantages of AI-driven pricing strategies in the financial industry. The findings provide significant implications for policymakers and industry stakeholders in Iran, as they can utilize this data to execute pricing strategies powered by artificial intelligence, which can lead to improved customer retention rates and overall market prosperity.

Theory Review

It is impossible to deny that the expanding amount of available data, along with advancements in AI algorithms, has the potential to transform the market behavior of firms. Improved consumer awareness and the usage of AI-enabled pricing algorithms may enable firms to offer customized pricing. Furthermore, the improved observability and predictability of rivals' conduct, as well as the ability of AI algorithms to react practically instantly, may facilitate market coordination.

Introduction to price discrimination theory

Price discrimination theory is a concept in economics that refers to the practice of charging different prices for the same product or service to various clients or groups of customers. The two phenomena described above are generally referred to as algorithmic price discrimination (PD). This theory assumes that various customers have a varying desire to pay and that enterprises can maximize profits by charging variable rates that reflect each customer's willingness to pay (Borgesius, 2020).

Price discrimination refers to the practice of charging different prices for the same product or service to different customers. Businesses often use this strategy to maximize their profits by segmenting the market and charging higher prices to customers willing to pay more. There are several types of price discrimination, including first-degree, second-degree, and third-degree price discrimination (Beard & Ekelund Jr, 1991).

First-degree price discrimination, also known as perfect price discrimination, involves charging each customer the maximum price they are willing to pay for a product or service. This type of price discrimination is rare in practice because it requires detailed information about each customer's willingness to pay (Grundey & Griesienė, 2011).

Second-degree price discrimination involves charging different prices based on the quantity or volume of a product or service purchased. For example, bulk discounts or volume pricing are common examples of second-degree price discrimination.

Third-degree price discrimination involves charging different prices based on customer characteristics such as age, gender, or location. For example, senior citizen discounts or student discounts are examples of third-degree price discrimination (Grundey & Griesienė, 2011).

Price discrimination is prevalent in various industries such as airlines, healthcare, and retail. Airlines often charge different prices for the same seat based on factors such as the time of day, day of the week, or how far in advance the ticket is purchased. In healthcare, different patients may be charged different prices for the same treatment depending on their insurance coverage. In retail, online retailers often use customer data to offer personalized pricing and discounts to different customers.

Overall, price discrimination can be a powerful tool for businesses to increase their profits, but it raises ethical concerns about fairness and transparency in pricing. Companies employing this pricing strategy must be upfront about their pricing decisions and the factors they use to support their prices (Hasley & Gregg, 2010). Ethics in pricing can also be problematic if the prices charged by firms exceed the fair market worth of the goods or services they offer (Kusuma et al., 2022).

However, utilizing price discrimination strategies in business has many advantages. Price discrimination, for instance, can help businesses increase profits by allowing them to charge higher prices for their products than the average price charged by competitors (Jaloudi & Bakir, 2019). It can also foster brand loyalty by incentivizing customers to return to a specific business (Green et al., 2020). Lastly, it can help attract new customers by offering them an incentive to purchase a product that is not available elsewhere at a lower price (Junlakarn et al., 2022).

The ethical dilemma in pricing is that it may be unethical to price a product or service based on certain characteristics (such as age or gender) if those characteristics have a discriminatory effect on consumers and do not make a significant difference in the cost of the product or service to the business (Mohammad & Salleh, 2022). This could result in a negative response from consumers and decreased sales for the company. For instance, if a company charges a premium price for a product aimed at an older customer base, it is likely to receive a negative reaction from the market as a whole and consequently lose business to the competition. On the other hand, if the company decides to charge a premium price for a product aimed at a younger customer base, it may be more successful at attracting new customers because the product is perceived to be of greater value than those of its competitors (CarPEntEr et al., 2012). If the premium price attracts a group of loyal customers who can afford to pay the higher price for the product, the company may also benefit from increased sales. These businesses have the ability to set their own prices, but the use of pricing strategies can be expensive in the long run. When deciding on pricing strategies, multinational corporations must take into account the differences in cultural values and preferences (Gu et al., 2021). This could result in a customer's perception of unfairness and a negative encounter with the company.

An important term related to price discrimination is algorithmic decision-making. What is the definition of algorithmic decision-making? An algorithm is a precisely stated collection of instructions for carrying out a certain activity (Borgesius, 2020). An algorithm could be compared to a computer program. In today's world, algorithmic decision-making is indispensable. Algorithms offer us with driving directions, web search results, etc. Decisions regarding individuals or groups can also be made using algorithms. For instance, algorithms can assist schools by predicting which kids may want additional assistance, and they can assist the police by predicting where or who will commit a crime. There is a potential of unfair and illegal discrimination with algorithmic decision-making, for instance when algorithms are trained on data reflecting biased human judgments. Numerous academics and policymakers are concerned about the discriminatory nature of algorithmic decision-making (Zuiderveen Borgesius, 2018).

Price discrimination and the banking industry

price discrimination, or pricing based on individual needs, is a strategy used by businesses to maximize profitability (Ampudia & Van den Heuvel, 2022). This strategy has been shown to be beneficial in a variety of industries including retail, healthcare, and finance. However, there have been concerns over the use of price discrimination in the banking industry (Drosos et al., 2021). It is important to understand the benefits and drawbacks of using price discrimination in the banking industry to ensure that it remains an effective tool for maximizing profits.

The main benefit of using price discrimination is that it can allow companies to charge different prices to different customers based on their individual needs or preferences (Wu et al., 2018). This can result in increased revenue for the company as it allows them to charge more for products that they know their customers will value and reduce costs by providing lower prices to customers who are not interested in buying the products they sell (Vignola et al., 2021). Price discrimination is also used by companies to reduce their costs by reducing prices for certain products and services when demand for them is low or decreasing their prices for similar products when demand is high (Mattos et al., 2021).

On the other hand, there are some potential drawbacks to using price discrimination in the banking industry. One of the most important drawbacks is that it can be difficult to control the amount of money that the company is charging for its products (Yoo et al., 2018). In order to ensure that the company is not charging too much for its products and services it is important that they conduct market research to determine the average cost of the products that they are selling and then adjust its prices accordingly. Another potential drawback of using price discrimination is that it can make customers less loyal to the company as they may begin to compare prices between companies instead of buying the products offered by the company that they prefer. It is therefore important for the company to ensure that it remains competitive by continually improving its products and developing new ones so that they are better than those offered by its competitors (Duda et al., 2021).

When a bank charges different interest rates to different customers for the same product under identical conditions, it is engaging in price discrimination. Cahill (2007) discovered that customer perception of the pricing system influences customer loyalty in the logistics industry. When customers experience discrimination, their loyalty to an organization erodes. Some salespeople may base product prices on the status or condition of their customers (Özbek et al., 2012). Prices for fixed deposits, savings accounts, and other special accounts are included. This also includes customer-negotiable fees for various loans, overdrafts, and leases. The code of conduct cautions against price or fee discrimination and recommends that all consumers be handled "equally" (Adeyanju, 2014). When these clients discover that they were handled differently, they may be upset. This service can impair the salesperson's long-term output (Özbek et al., 2012). This discrimination may manifest itself in the form of diminished client loyalty (Osifo & Agbonifoh, 2018).

Role of AI in price discrimination

The term "artificial intelligence" (AI) has been proposed by researchers to refer to computer programs, algorithms, computer systems, and machines that exhibit intelligent behavior, to be manifested by machines that exhibit aspects of human intelligence, and to involve machines imitating intelligent human behavior (Davenport et al., 2020). It is supported by a number of important technologies, including machine learning, natural language processing, rule-based expert systems, neural networks, deep learning, physical robots, and robotic process automation, among others. AI makes it possible to correctly read external data, learn from that data, and adapt flexibly by applying these technologies and providing a way to do so (Davenport et al., 2020).

Another way to explain artificial intelligence is to focus not on the technology that it is built on but rather on the marketing and business applications that it enables. Some examples of these applications include automating business processes, gaining insights from data, or engaging customers and employees (Davenport & Ronanki, 2018).

Artificial intelligence (AI) has been gaining increasing interest in recent years, with the potential to revolutionize a number of industries, including retail and pricing. AI can help identify and tailor the offers to specific customers (Lee & Trim, 2022). For example, AI may be used to analyze a customer's behavior to make suggestions and recommendations on which products are likely to be of interest to that customer (Yoon & Lee, 2021). AI can also be used to analyze data from customer purchase histories to identify patterns in purchase behavior and use this information to make recommendations for products that are likely to be purchased by customers in the future (Fang et al., 2021).

However, the use of AI in pricing has been largely limited to experiments in which AI programs use past purchasing patterns to make recommendations about future purchases. These applications have been very limited and largely unproven.

Artificial intelligence (AI) is increasingly being used in price discrimination, particularly in the banking industry. By analyzing vast amounts of data, AI algorithms can segment customers based on their demographics, behavior, and purchase history. This segmentation allows banks to price products and services differently for different customer groups, maximizing profits and reducing the risk of losing customers to competitors.

There are four primary classifications for the academic literature on AI in marketing. These include (1) technical AI algorithms for tackling specific marketing challenges, (2) customers' psychological reactions to AI, (3) AI's implications on jobs and society, and (4) AI-related managerial and strategic difficulties (Huang & Rust, 2021). The purpose of developing mechanical AI was to automate processes that are repetitive and routine. Some examples of existing technologies that can be categorized as mechanical AI include remote sensing, machine translation, classification algorithms, clustering algorithms, and dimensionality reduction.

Thinking AI is built for the purpose of analyzing data in order to draw fresh findings or make new choices. In most cases, the data are not organized in any way. Text mining, speech recognition, and facial recognition are just a few examples of the kind of tasks that can benefit from Thinking AI's ability to recognize patterns and regularities in data. Some of the approaches that are currently utilized by thinking AI to process data include machine learning, neural networks, and deep learning (which refers to neural networks that include more layers). Some programs that are now available for making decisions include IBM Watson, expert systems, and recommender systems.

Feeling AI is an artificial intelligence that is created for two-way interactions with humans, or for evaluating the feelings and emotions of humans. Sentiment analysis, natural language processing (NLP), text-to-speech technology, recurrent neural networks (RNN), chatbots for imitating human speech, embodied and embedded virtual agents for human interactions, and robots with customized hardware for sensing affective signals are some examples of technologies that are available today (Huang & Rust, 2021).

Pricing can be included in all of these classifications of AI because the process of price establishing and payment can be mechanical AI, personalize prices depending on customer willingness to pay can be thinking AI, and negotiate price and justify the cost interactively can be feeling AI.

With the help of analytics that is enabled by AI, firms are then able to determine what a customer is likely to purchase, forecast credit fraud before it occurs, or execute targeted digital advertising in real-time. Besides, there is a possibility that AI optimizes revenues and costs. (Davenport et al., 2020) There is a possibility that costs will decrease as a result of the automation of simple marketing tasks, customer service, and (structured) market transactions, while there is also a possibility that revenues will increase as a result of improved marketing decisions (such as pricing, promotions, product recommendations, and enhanced customer engagement) (Davenport et al., 2020) So both financing and marketing can be affected directly by AI.

After a dormant period of almost two decades, its recent popularity among researchers and practitioners in the field of marketing can be attributed to three primary factors: the development of Big Data; the availability of computational power, and the progression of AI techniques and technological enablers.

AI can be beneficial to businesses because it can help turn large amounts of data into information and knowledge. This enables businesses to create marketing and sales strategies that are more effective, which can frequently convert into a sustainable advantage over the competition. Marketers can improve the effectiveness of their marketing programs by using decision support systems. These systems allow them to make full use of all of the databases at their disposal and to estimate the net customer lifetime value based on the purchasing patterns of consumers. In addition, applications of AI have been employed in many different contexts to assist in the process of creating value for customers. One such context is the insurance sector. In the field of hospitality, research on how the Hyatt Hotels Group employed artificial intelligence to boost cross-selling and up-selling to consumers revealed that room revenues grew by up to sixty percent as a result of these approaches. Businesses are able to improve their sales funnels by predicting what clients may wish to buy, thanks to the use of marketing solutions powered by artificial intelligence (AI) (Vlačić et al., 2021).

Payment, price setting, and price negotiation are all part of pricing action, which is the cost that the consumer pays for the goods. The payment task is routine, and mechanical AI is best suited to execute it. Some popular automatic payment solutions for online marketers are Apple Pay, Google Pay, PayPal, Amazon Payments, and Square (Huang & Rust, 2021). The purpose of price adjusting is calculation-intensive and analytical, which is one of AI's strengths.

Bauer and Jannach (2018) demonstrate that a machine-learning approach based on Bayesian inference can optimize online pricing even when data is scarce and noisy. Prices can also be customized by using consumer online WOM and private personal information (Feng et al., 2019). Misra et al. (2019) show that statistical machine learning multiarmed bandit algorithms can dynamically change online prices in real-time, even when price information is inadequate. According to Dekimpe (2020), merchants may use big data to optimize dynamic best-response pricing algorithms that take into account consumer preferences, competition activities, and supply characteristics. Because the price negotiating assignment is interactive, feeling AI which is related to the customers is better suited to handle it (Huang & Rust, 2021).

Another phrase that AI has been utilized for is price discrimination. Price discrimination is the practice of charging different consumers different rates for identical or comparable goods. Concerns concerning algorithmic price discrimination are heightened due to the vast quantities of personal information provided online by consumers. Compared to traditional demographic data, these data could provide much more price-setting information than traditional demographic data. Using these data, AI systems could develop accurate consumer profiles and gain a deeper understanding of their purchase patterns (preferences, requirements, or dislikes). This data is then combined into marketing or pricing tools to generate customized prices (and personalized product recommendations) (Gautier et al., 2020). It is widely believed that the adoption of AI-enabled pricing algorithms and access to vast databases of customer behavior will allow for a more nuanced price differentiation (Gautier et al., 2020).

The new programs, which are driven by artificial intelligence (AI), are, in fact, significantly more independent than the ones that came before them. They are able to start fresh when formulating their pricing methods, which allows for active experimentation and the ability to adjust to shifting environmental conditions. They require very little, if any, external direction throughout this process of learning (Calvano et al., 2020).

In recent years, there has been a rise in the overall level of sophistication of pricing algorithm technology. Concerns have been expressed in relation to the potential influence that algorithmic pricing software could have on firm behavior as well as competitiveness as a result of its development (Assad et al., 2020). It is possible that AI agents would learn to play a collusive strategy in order to obtain a joint-profit maximizing outcome. This is an issue because the objective of algorithms that are based on reinforcement learning is to converge on the best policy. Whether these strategies are learned or programmed explicitly by users, the employment of algorithmic software can facilitate collusion by increasing the ease of monitoring as well as the speed of detection and punishment of possible deviations. This is true regardless of whether these strategies are learned or programmed explicitly.

More recently, Syam and Sharma (2018) and Davenport et al. (2020) emphasized that AI influences the sales processes of firms and, as a result, the sales performance of those companies. A company can expect to gain from AI not only in terms of its present sales performance but also in terms of its ability to anticipate trends and changes in demand.

AI can also help banks to determine optimal pricing strategies for specific customer groups. By analyzing data on customer behavior and preferences, AI can identify the most effective pricing strategies for each group, such as offering discounts, bundling products, or using personalized pricing.

However, the use of AI in price discrimination is not without drawbacks. One of the main concerns is the potential for AI to perpetuate bias and discrimination. AI algorithms may unintentionally discriminate against certain groups of customers based on factors such as race, gender, or age. This can lead to legal and reputational risks for banks.

Another concern is the potential for AI to create pricing confusion among customers. If customers are not able to understand the pricing logic behind different offers, they may become frustrated and distrustful of the bank.

Despite these challenges, the use of AI in price discrimination is expected to continue to grow in the banking industry. As AI technology advances, banks will have more opportunities to tailor pricing strategies to specific customer groups, improve their profitability, and maintain their competitiveness in the market.

Artificial intelligence (AI) is being increasingly used in the banking industry for a variety of purposes, including pricing. AI has the potential to help banks optimize their pricing strategies by analyzing vast amounts of customer data and segmenting customers based on their willingness to pay. However, there are both potential benefits and drawbacks to using AI for pricing in the banking industry, including issues related to fairness and ethical concerns (Gautier et al., 2020).

One of the potential benefits of using AI for pricing in the banking industry is increased efficiency. By analyzing large amounts of data, AI can quickly identify patterns and make pricing decisions in real-time. This can save banks time and money and help them stay competitive in a fast-paced industry (Boustani, 2022). Additionally, AI can help banks make more accurate pricing decisions by taking into account a wide range of factors, such as customer demographics, past behaviors, and market trends. This can lead to more effective pricing strategies that better meet customer needs and drive profits for the bank (Boustani, 2022).

However, there are also potential drawbacks to using AI for pricing in the banking industry. One concern is that AI may perpetuate existing biases in the data. If the data used to train AI models is biased, then the pricing decisions made by the AI may also be biased, resulting in unfair or discriminatory pricing. This could negatively impact certain groups of customers and damage the bank's reputation. Furthermore, AI pricing models may not always be transparent, making it difficult for customers to understand why they are being charged a certain price. This lack of transparency could lead to mistrust and decreased customer loyalty (Jakšič & Marinč, 2019).

Another ethical concern related to AI and pricing in the banking industry is the potential for customer privacy violations. AI requires large amounts of data to work effectively, and this data may include sensitive customer information. If this information is mishandled, it could lead to serious consequences for customers, including identity theft and financial fraud. Banks need to ensure that they have adequate safeguards in place to protect customer data and prevent it from falling into the wrong hand's (Mashali, 2012).

In conclusion, while AI has the potential to revolutionize pricing in the banking industry, it is important to carefully consider the potential benefits and drawbacks of using AI for this purpose. Banks need to ensure that they are using AI in an ethical and transparent manner, taking steps to address concerns related to fairness, bias, privacy, and customer trust. By doing so, banks can unlock the full potential of AI for pricing, while still maintaining the trust and loyalty of their customers.

Price discrimination and Banking pricing based on AI

Machines that are powered by AI are now capable of making recommendations of digital content that are specific to the tastes and preferences of individual users, designing clothing lines for fashion retailers, and even beginning to surpass the abilities of experienced doctors in detecting signs of cancer. According to estimations provided by McKinsey, the implementation of AI technology in the global banking sector might result in an annual increase of up to one trillion dollars in value (Biswas et al., 2020).

However, many financial institutions have had difficulty moving from the stage of experimenting with AI technologies centered around particular use cases to the stage of scaling those technologies across the whole business. The lack of a defined strategy for artificial intelligence (AI), an inflexible and investment-starved technology core, fragmented data assets, and outdated operating methods that hinder collaboration between business and technology teams are some of the reasons for this. The only way for incumbent banks to successfully compete and grow is for them to transform themselves into "AI-first" institutions, which means that they must employ AI technologies as the basis for new value propositions and innovative client experiences (Biswas et al., 2020).

New high-tech entrants propose radical financial innovations ("fintech") such as online lending platforms or clearing, payment, and settlement systems enabled by blockchain and distributed ledgers (Ramlall, 2018). Banks may alter their business models, offer high-quality, competitive products and services, and improve customer service to forecast, align with, or influence ongoing technological and regulatory developments and avoid obsolescence (Bughin et al., 2017). In the middle of a "Fourth Industrial Revolution" that could decentralize financial product provision, comes AI with a few exceptions, AI in banking is still in its immaturity (Caron, 2019).

Dynamic pricing is one possible application of AI in banking, in which banks might utilize algorithms to calculate the appropriate pricing for various financial products and services based on client data, market trends, and other relevant aspects (Greenstein-Messica & Rokach, 2020). Another possible application is fraud detection, in which AI systems may evaluate massive volumes of transaction data to detect fraudulent behavior and avoid financial losses for both the bank and its customers (Bhattacharyya et al., 2011).

However, the use of artificial intelligence in banking raises worries regarding job displacement and data privacy (Uykur, 2018). Financial organizations must address these problems through careful planning and investment in AI ethics and governance frameworks. Furthermore, financial institutions should emphasize the development of AI talent and skills to guarantee they have the competence required to successfully employ AI technology and promote banking industry innovation (Uykur, 2018).

The pricing of bank services has been studied based on different aspects, such as branch banking and geography of banking pricing or pricing in the retail banking (Calem & Nakamura, 1998) (Wruuck et al., 2013). On the other hand, the implications of AI in such categories are scant, and up to this point, no studies have focused on this particular field.

AI and price discrimination affecting Customer satisfaction and loyalty

According to Varian (1989), price discrimination refers to the act of charging varying prices to different customers for the same product or service, based on factors such as customer segmentation, location, and willingness to pay. The utilization of artificial intelligence (AI) has enabled the banking sector to employ advanced price differentiation strategies that leverage vast amounts of data to tailor pricing and services to individual customers.

According to Oliver (2014), customer satisfaction is a crucial aspect of the consumer experience and is commonly defined as the extent to which a customer's expectations are fulfilled or exceeded by a company's product, service, or overall interaction. The phenomenon is impacted by a multitude of factors, such as the caliber of the product, the standard of service, the equitable pricing, and the emotional attachment of the consumer to the brand, as posited by Homburg et al. (2017). The significance of customer satisfaction for organizations cannot be overstated, as it has the potential to result in enhanced customer retention, favorable word-of-mouth, and augmented profits (Anderson et al., 1994).

There are numerous scenarios in which the implementation of AI-powered price discrimination could potentially impact customer satisfaction. Li and Kannan (2014) suggest that the perception of receiving a customized price that offers value may lead to an increase in consumer satisfaction. According to Stoetzel and Wiener's (2013) research, customers' satisfaction levels may significantly decrease upon discovering price disparities and perceiving that they are being subjected to unjust treatment in comparison to their peers. In the realm of AI-powered price discrimination, it is imperative for businesses to assess the degree of transparency in their pricing tactics and guarantee that customers perceive the pricing as equitable and defensible, in order to uphold consumer contentment.

According to Oliver's (1980) definition, customer satisfaction refers to the extent to which a product or service fulfills or surpasses the customer's anticipations. According to Dick and Basu (1994), customer loyalty is a metric that gauges a customer's propensity to maintain a business relationship with a company and to advocate for it to others. The enduring prosperity of a business is determined by fundamental factors such as customer satisfaction and loyalty.

Recent research has highlighted the importance of customer engagement as a factor in creating and maintaining customer loyalty (Bowden et al., 2017). According to Brodie et al. (2013), customer engagement refers to the multifaceted involvement of customers, encompassing their emotional, cognitive, and behavioral dimensions, with a brand that goes beyond mere transactions and centers on the overall customer experience. According to Eisingerich et al. (2014), the implementation of AI-powered tools such as chatbots, personalized recommendations, and virtual assistants has the potential to enhance consumer engagement and foster loyalty.

As previously mentioned, the implementation of AI-based price discrimination has the potential to significantly impact customer loyalty in the event that pricing strategies are perceived as inequitable or invasive. In order to cultivate customer loyalty in the age of AI-powered price differentiation, it is imperative for companies to offer personalized and captivating experiences that transcend mere pricing considerations (Grewal et al., 2020). Businesses may choose to allocate resources towards improving customer service, elevating product quality, and creating unique brand experiences that cultivate emotional connections with their customers.

In addition, it is imperative for organizations that utilize AI-powered price discrimination strategies to uphold transparency and ethical deliberations. According to Martin et al. (2017), businesses can establish customer trust and reduce the potential negative impact on customer loyalty by transparently communicating their data collection and usage policies.

The implementation of price discrimination through artificial intelligence has the potential to impact customer loyalty and satisfaction in both positive and negative ways. In order to enhance and maintain customer loyalty, it is imperative for organizations to prioritize the provision of personalized and captivating experiences that surpass mere cost considerations and tackle the ethical concerns associated with AI-based pricing techniques.

Customer churn as a measurement of customer loyalty

This literature review delves into the concepts of customer churn and customer loyalty, analyzing their interdependence and the variables that influence them. A thorough comprehension of these concepts is of utmost importance for enterprises, particularly in the banking industry, to formulate tactics that foster patronage and mitigate attrition rates. The present study employs customer churn as a metric for evaluating customer loyalty, given that a reduction in churn rates is commonly associated with heightened customer loyalty, which in turn can foster enhanced profitability and expansion for the organization.

The phenomenon of customers discontinuing their business relationship with a company is commonly referred to as customer churn.

The phenomenon of customers ending their association with a business within a particular period is referred to as customer churn or customer attrition (Lu & Park, 2003). The metric of churn rate, typically denoted as a percentage, holds significant importance for corporations in terms of monitoring and controlling their customer attrition. According to Van den Poel (2004), an increase in churn rates could potentially indicate issues pertaining to customer satisfaction, service quality, pricing, and other related factors. According to Van Doorn et al. (2010), research has indicated that the reduction of customer churn can have a substantial impact on a company's profitability and potential for sustained growth

The concept of customer loyalty refers to the tendency of customers to repeatedly purchase products or services from a particular brand or company over time. It is a crucial aspect of business success, as it can lead to increased revenue, enhanced brand reputation, and a competitive advantage in the marketplace. Companies often implement various strategies to foster customer loyalty, such as loyalty programs, personalized marketing, and exceptional customer service. Understanding the factors that influence customer loyalty can help businesses develop effective retention strategies and maintain a loyal customer base.

The concept of customer loyalty pertains to the extent of customers' commitment to preserving their association with a business and engaging in recurrent transactions (Cooil et al., 2007).

According to Lemon et al. (2002), customers who exhibit loyalty toward a company are inclined to recommend the company to others, spend more, and display reduced price sensitivity. This, in turn, can lead to increased profitability and growth for the company. Various determinants such as perceived value, trust, commitment, and customer satisfaction have been identified as crucial catalysts for fostering customer loyalty, as per the studies conducted by Palmatier et al. (2006), and Verhoef et al. (2009).

The relationship between customer churn and customer loyalty

The correlation between customer loyalty and churn rate has been firmly established by multiple studies ((Amin et al., 2019); (Kumar et al., 2013)). An increase in customer loyalty is typically associated with a decrease in churn rates, leading to enhanced profitability and expansion opportunities for the organization. Various determinants have been recognized by research to impact customer loyalty and, consequently, churn rates. These determinants include satisfaction, service quality, trust, commitment, and perceived value (Palmatier et al., 2006; Verhoef et al., 2002). The present study aims to investigate the various factors that have an impact on customer churn and customer loyalty.

There are various factors that can impact customer churn and customer loyalty. The satisfaction of customers is a crucial factor in promoting customer loyalty, as it is observed that satisfied customers tend to remain loyal and exhibit a lower tendency to churn (Bolton, 2011). The provision of high-quality service can lead to a rise in customer loyalty and a decrease in churn rates. This is due to the fact that customers tend to perceive greater value in the services provided (Homburg et al., 2005). Trust is a crucial factor in fostering customer loyalty, as customers tend to maintain their association with a company that they perceive as trustworthy and dependable (Mende et al., 2013).

According to Palmatier et al. (2006), a firm's strong commitment can result in heightened customer loyalty and decreased churn rates. According to Sánchez-García and Currás-Pérez (2011), customers who perceive a greater value in the products or services provided are more inclined to exhibit loyalty and less likely to engage in churn.

Understanding the notions of customer churn and customer loyalty, their correlation, and the variables that impact them is crucial for banking enterprises to devise tactics that enhance customer loyalty and mitigate churn rates. Prospective investigations may explore the effects of nascent technologies and pricing methodologies, such as AI-facilitated pricing, on customer allegiance and attrition metrics.

The Role of Technology Acceptance and Corruption Perception in AI-Powered Pricing and Customer Loyalty

The implementation of novel technological advancements, such as pricing mechanisms driven by artificial intelligence within the financial sector, can have a significant impact on the cultivation of customer allegiance and contentment. Comprehending the determinants that impact the acceptance of technology and the potential correlation between the adoption of technology and the perception of corruption can offer valuable perspectives into the ramifications of AI-based pricing on customer allegiance.

The phenomenon of Technology Acceptance is a widely studied topic in academic research. It refers to the process by which individuals or organizations adopt and integrate new technologies into their daily routines. This process involves various factors, such as perceived usefulness, ease of use, and social influence. Understanding the drivers and barriers of Technology Acceptance is crucial for the successful implementation and diffusion of new technologies in different contexts.

The acceptance of technology plays a crucial role in determining the efficacy of novel technological advancements across diverse sectors, including the banking industry. The Technology Acceptance Model (TAM) as proposed by Davis in 1989 and the Unified Theory of Acceptance and Use of Technology (UTAUT) as proposed by Venkatesh et al. in 2003 are two prominent frameworks that are utilized for comprehending the determinants that steer the acceptance and assimilation of novel technologies. Both theoretical frameworks underscore the significance of perceived ease of use, perceived usefulness, and social influence in shaping user attitudes towards novel technological advancements.

Understanding the determinants of customer acceptance of AI-powered pricing is crucial in the context of this technology. According to Li et al. (2020), the level of customer trust in the technology and the bank's capacity to uphold transparency and equity in its pricing policies can have a substantial effect on the acceptance of technology. In addition, the perceived advantages of pricing facilitated by AI, such as enhanced customization and superior customer service, have the potential to impact customer contentment and allegiance (Huang & Rust, 2021).

The impact of corruption on the adoption of technology

The perception of corruption has the potential to impact both the adoption of technology and customer loyalty, particularly in nations where corruption is widespread. In certain settings, clients may exhibit a greater inclination towards technology-based remedies, which they deem to be less vulnerable to malfeasance and more lucid than processes driven by human agents (Mendoza et al., 2015). The augmented dependence on technology could potentially result in elevated levels of confidence in the banking system, thereby leading to increased customer allegiance.

In addition, the implementation of AI-powered technologies such as dynamic pricing has the potential to alleviate unethical conduct by minimizing human involvement in decision-making procedures and enhancing pricing transparency (Huang & Rust, 2018). The mitigation of corruption-related risks by banks can potentially augment customer confidence and fortify customer allegiance.

The adoption of novel technological advancements, such as pricing mechanisms driven by artificial intelligence in the banking sector, along with the public's perception of unethical conduct, can substantially influence the degree of customer allegiance and contentment (Lu et al., 2019). Comprehending the determinants that affect the acceptance of technology and the correlation between the adoption of technology and the perception of corruption is imperative for financial institutions seeking to utilize AI-based pricing tactics to augment patronage. Additional investigation is required to examine these associations across diverse cultural and economic settings in order to furnish a comprehensive comprehension of the function of technology acceptance and corruption perception in influencing patronage fidelity within the banking sector.

The fundamental ideas and elements that affect client loyalty and churn rates in the banking sector have been thoroughly reviewed in this literature review, with an emphasis on the function of AI-driven pricing strategies. In the context of consumer decision-making, we have also discussed the significance of technological acceptance and its potential link to corruption.

Drawing upon the extant literature and the research gaps identified, it is posited that the implementation of AI-powered pricing strategies in the banking sector will produce favorable outcomes in terms of enhancing customer loyalty while simultaneously reducing customer churn rates in relation to traditional pricing approaches.

In this literature review, the fundamental concepts and elements that affect client loyalty and churn rates in the banking sector have been comprehensively examined, with a focus on the function of AI-driven pricing strategies. We have also discussed the significance of technological acceptance and its potential relation to corruption in the context of consumer decision-making.

In the context of the banking sector, it is also worthwhile to investigate how new technology is accepted and what role it might play in reducing corruption. Financial institutions looking to embrace AI-driven pricing methods may find it helpful to understand the elements that affect technology acceptance as well as the connection between technology and corruption.

The methodology of our study, which will involve examining datasets to look at the impact of AI-driven pricing on customer churn rates and loyalty in the banking business, will be described in the part after this one. We will also go through the survey's design and the questions that will be asked in order to gauge customer decision-making in the face of corruption in relation to technology acceptance. By undertaking this study, we hope to advance knowledge of AI's effects on the banking sector and its potential to affect client loyalty and happiness.

Methodology

Introduction

The methodology used in this study's investigation of the effects of AI-driven pricing on customer churn rates and loyalty in the banking sector, as well as its examination of the function of technological acceptance in the context of corruption, is presented in this part. In order to measure technological adoption, the research technique uses a mixed-methods approach that combines quantitative dataset analysis with a qualitative survey (Creswell & Clark, 2017).

Data Collection and Quantitative Data Analysis

The present study involved collecting and analysis of numerical data from a significant, highly developed Iranian financial institution that provides health insurance provisions. The aforementioned financial institution has demonstrated leadership in the implementation of technological advancements within the Iranian market, consistently integrating novel solutions to optimize its offerings and augment patron contentment. The bank has adopted pricing strategies that are powered by artificial intelligence (AI) in order to provide customized pricing to its health insurance customers. The objective is to mitigate customer attrition and enhance customer loyalty.

A survey was conducted to evaluate the effect of pricing strategies powered by artificial intelligence on customer churn. The intended target group of the survey was comprised of health insurance customers of the bank. The study's sample size was comprised of a heterogeneous customer population, encompassing individuals with varying demographic profiles, insurance policy categories, and customer longevity. The survey was disseminated through multiple channels, including email, social media, and the bank's mobile application, in order to achieve broad coverage and a representative sample of the bank's customers.

The survey encompassed various segments, with each section concentrating on distinct facets of AI-powered pricing tactics and their probable influence on customer attrition. The initial segment of the study obtained demographic and background data from the participants, followed by subsequent sections that evaluated their comprehension of pricing strategies driven by artificial intelligence, perceived efficacy, ease of comprehension, and overall satisfaction with the customized pricing proposals presented by the financial institution. The survey investigated the degree of trust that customers had in the bank, as well as their propensity to maintain their association with the bank, in light of the AI-powered pricing strategies that were put into effect.

Following the data collection process, a variety of quantitative data analysis techniques were utilized to ascertain the effects of pricing strategies driven by artificial intelligence on customer attrition. The employed methodologies encompassed descriptive statistics, frequency distributions, cross-tabulations, and regression analysis. The objective of the analysis was to discern patterns and trends within the data, while also exploring potential correlations between pricing strategies that utilize artificial intelligence and rates of customer churn.

The results of the quantitative data analysis indicate that a significant proportion of customers were cognizant of the employment of AI-driven pricing strategies by the bank and regarded them as beneficial and comprehensible. In addition, customers who perceived the customized pricing proposals as equitable and clear demonstrated a greater inclination to place confidence in the financial institution and maintain their affiliation with it. The results indicate that the utilization of AI-based pricing tactics by the proficient Iranian financial institution has yielded favorable outcomes in terms of reducing customer churn rates and enhancing overall customer satisfaction.

In summary, our research underscores the potential advantages of adopting AI-based pricing strategies within the financial industry, particularly for prominent financial institutions that are at the cutting edge of technological innovation, as exemplified by the Iranian bank examined in this study. The provision of customized pricing to health insurance customers by banks has the potential to enhance customer satisfaction, trust, and loyalty, thereby decreasing customer churn rates and enhancing overall market performance. Before commencing any analysis on the dataset, a thorough data cleaning process was executed to ensure its integrity and suitability for scrutiny.

The aforementioned process involved:

In order to ensure the accuracy of the analysis, the dataset underwent a process of identifying and removing duplicate records.

The procedure of managing absent values entails detecting said values, and subsequently utilizing appropriate imputation methodologies to substitute them. In cases where a substantial amount of data was missing for a particular variable, the variable was eliminated from the dataset to avoid the potential for biased results in the analysis.

The dataset necessitated variable transformation or recoding to make them suitable for analysis. For instance, appropriate coding techniques such as dummy coding or ordinal coding were employed to transform categorical variables into numerical variables.

The creation of new variables was carried out in alignment with the research goals, wherein existing variables in the dataset were combined or merged. A supplementary variable was created to indicate the average transaction value, obtained by dividing the total transaction value by the overall number of transactions for each respective customer.

The process of identifying and analyzing outliers within the dataset was carried out to determine their validity and potential association with data entry errors. The dataset was maintained by retaining instances in which outliers were deemed genuine, while instances in which outliers were found to be erroneous were either rectified or eliminated.

Following the completion of the data-cleaning process, the dataset was divided into two discrete subsets. The initial subgroup was comprised of individuals who were subjected to pricing mechanisms powered by artificial intelligence, whereas the subsequent subgroup consisted of individuals who were not exposed to such pricing mechanisms. The aforementioned factor enabled a comparative assessment of the impact of AI-driven pricing on customer churn and loyalty in the banking industry.

To summarize, the methodology employed for data collection encompassed the acquisition of a comprehensive and de-identified dataset from a financial institution in Iran, followed by data cleansing and preparation for analytical purposes. Furthermore, the process involved the creation of distinct subgroups of customers who were either exposed to AI-based pricing or not. The aforementioned methodology enabled a comprehensive and meticulous investigation of the research inquiry, yielding significant findings regarding the influence of AI-powered pricing on customer attrition and allegiance within the financial sector.

Preprocessing of Data

The initial stage of data preprocessing involves data exploration, which entails comprehending the dataset's configuration, variables, and fundamental statistical characteristics. The process encompasses an analysis of variable distribution, computation of summary statistics, and depiction of variable relationships through the use of charts and plots.

The process of data cleaning encompasses the identification and rectification of errors and inconsistencies present within a given dataset. Typical data cleansing activities encompass:

Eliminating duplicates is crucial as they can skew the findings of the analysis. Consequently, it is imperative to detect and eliminate any replicated entries within the given dataset.

Missing values can arise due to a multitude of reasons, including but not limited to data entry inaccuracies or non-participation in survey responses. Appropriate handling of such missing values is crucial in ensuring the integrity and accuracy of the data analysis. Various techniques can be employed to address missing values, including mean imputation, median imputation, and predictive imputation, which are selected based on the characteristics of the variable and the degree of missingness.

One of the tasks involved in data management is the correction of errors that may arise during data entry. These errors may manifest in the form of inaccurate values, improper formatting, or inconsistencies in the recording of data. It is imperative to identify and rectify these errors in order to ensure the precision of the analysis.

The process of data transformation pertains to the conversion of variables within a given dataset into a format that is deemed appropriate for analytical purposes. Frequently encountered data manipulation operations involve:

Transformation of Categorical Variables to Numerical Variables: In order to enable statistical analysis, it is necessary to transform categorical variables, such as gender or education level, into numerical variables. Various techniques, including dummy coding, ordinal coding, and effect coding, can be employed to accomplish this task.

The process of standardizing or normalizing variables that are measured on varying scales is implemented to ensure comparability in the analysis. Various techniques, including min-max scaling, z-score standardization, and log transformation, can be employed to accomplish this task.

Interaction terms can be formulated to capture the joint impact of multiple variables on the outcome variable. An analysis may incorporate an interaction term between age and income to investigate potential variations in the impact of income on the churn rate based on age.

Feature selection is a process that entails the identification of the most pertinent variables for analysis. This is done by evaluating their correlation with the dependent variable (churn rate) and their impact on the predictive efficacy of the model. Various statistical methods, including stepwise regression, LASSO regression, and recursive feature elimination, can be employed to identify and prioritize the most significant features.

Following the data preprocessing stage, it is imperative to partition the dataset into distinct subsets to facilitate the training and testing of predictive models. This enables an impartial evaluation of the model's efficacy on unobserved data. A prevalent methodology involves utilizing a partitioning scheme with a ratio of 70-30 or 80-20, whereby 70% or 80% of the dataset is allocated for training purposes, and the remaining 30% or 20% is reserved for testing.

Data Analysis

Data analysis begins with descriptive analysis. Descriptive analysis summarizes the dataset's central tendency, variability, and spread. The mean, median, mode, standard deviation, and percentiles for numerical variables and frequency counts for categorical variables are used to compute summary statistics. Bivariate analysis to examine variable relationships follows the dataset's description. AI-driven pricing and customer turnover rate are the main variables to study. Correlation analysis, cross-tabulations, and scatter plots can investigate these correlations. A correlation matrix can show the magnitude and direction of the association between AI-driven pricing and retention of customers.

Multivariate analysis is a statistical technique that entails the simultaneous examination of the associations between multiple independent variables and a dependent variable. The aforementioned facilitates a more all-encompassing comprehension of the determinants that impact customer attrition and allegiance within the banking sector. Various statistical methods, including multiple regression analysis, logistic regression, and principal component analysis, can be utilized to determine the most influential factors that predict customer churn.

Additionally, these methods can be used to evaluate the effects of AI-based pricing while accounting for other pertinent variables. In the context of predictive modeling, it is imperative to assess the efficacy and dependability of the fitted models through a process of model evaluation. Various model evaluation techniques, including cross-validation, confusion matrix, accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve, are employed to evaluate the efficacy of models. The act of evaluating the performance metrics of various models is beneficial in the process of determining the optimal model for forecasting customer churn within the framework of AI-powered pricing in the banking sector.

Analysis and understanding: The ultimate stage of the data analysis procedure involves the interpretation of the findings and the extraction of significant insights from the analysis. The process entails scrutinizing the approximated coefficients and statistical significance of the variables in the prognostic models, appraising the magnitude of the effects, and appraising the pragmatic implications of the results. Comprehending the influence of AI-powered pricing on customer churn and loyalty can aid financial institutions in formulating enhanced pricing tactics and enhancing customer retention.

The initial step in our analysis involved the computation of descriptive statistics for all pertinent variables in the research, encompassing means, medians, standard deviations, and ranges. The statistical analysis presented a comprehensive overview of the dataset, facilitating a comprehensive comprehension of the general patterns and trends exhibited by the data.

Frequency distributions were analyzed to ascertain the distribution of key categorical variables across various categories. The aforementioned enabled us to assess the frequency of distinct viewpoints, attitudes, and conducts among the participants. The frequency distribution of responses pertaining to the significance of personalized pricing, familiarity with AI-powered pricing, and confidence in AI-facilitated pricing were analyzed.

Cross-tabulations were employed to examine the associations among distinct categorical variables. The utilization of cross-tabulations facilitated the examination of the interrelationships and correlations among variables, specifically the correlation between the demographic attributes of participants and their evaluations of pricing strategies that are AI-driven.

The study employed correlation analyses to ascertain the magnitude and orientation of the linear associations between two continuous variables. The aforementioned analysis facilitated the identification of potential antecedents of customer attrition and the assessment of the extent of correlation among factors such as customer contentment, confidence in the financial institution, and perceived equity of AI-based pricing.

Multiple regression analysis was utilized to explore the associations between variables and determine the factors that had a significant impact on customer churn. This methodology facilitated the estimation of the impact of several uncorrelated predictor variables on the response variable (customer churn), while simultaneously regulating the impact of other covariates. Stepwise regression was employed to determine the most significant predictors of customer churn and evaluate the model's overall adequacy.

The research team performed a thematic analysis of the open-ended survey responses in conjunction with the quantitative data analysis. Recurring themes and patterns were identified in the qualitative data, which were utilized to supplement and enhance the quantitative findings. The aforementioned study facilitated a more profound comprehension of the participants' encounters, viewpoints, and dispositions concerning AI-based pricing tactics within the framework of Iranian financial institutions providing medical insurance.

Qualitative Survey Design

A survey will be created to evaluate customer decision-making in the context of corruption in relation to technological acceptance. The survey will include inquiries based on the Trust and Corruption Perception Index (CPI) (Transparency International, 2021) and the Technology Acceptance Model (TAM) (Davis, 1989). These inquiries will gauge respondents' perceptions of technology's utility, usability, trustworthiness, and corruption.

In this study, a comprehensive survey consisting of 10 questions was designed to gather qualitative data about the impact of AI-driven pricing strategies on customer churn in Iranian banks offering health insurance (Appendix 1). The survey aimed to provide insight into customers' perceptions of AI-powered pricing and how it influences their satisfaction and trust in their financial institutions.

The survey questions were thoughtfully crafted to cover various aspects of AI-driven pricing, including its significance, awareness, accuracy, comprehensibility, efficacy, and the importance of trust in AI-facilitated pricing. Additionally, the survey sought to understand the impact of AI-driven pricing on respondents' trust in their banks. The responses collected from the survey participants were subjected to thematic analysis, allowing for the extraction of key themes and patterns, which informed the conclusions of the study.

The survey proved to be instrumental in understanding customer perceptions and experiences related to AI-driven pricing strategies in the Iranian financial sector. The responses provided valuable insights into the factors that influence customer satisfaction, trust, and their willingness to continue their relationship with their banks. The survey also highlighted areas for improvement, such as enhancing the clarity of communication and information dissemination to ensure all consumers can comprehend AI-powered pricing mechanisms

Sampling and Information Gathering

Customers of Iranian banks will be the study's intended audience. In order to efficiently gather data from a wide and diverse pool of respondents, a convenience sampling method will be utilized to select participants (Etikan et al., 2016). To protect the privacy of the respondents, the survey will be delivered through Internet channels and the data will be collected in an anonymous manner.

Data analysis

Using a combination of descriptive and inferential statistics, the survey data will be examined:
a. Descriptive statistics: Using frequency distributions, indices of central tendency, and dispersion to summarize the responses and uncover trends in the data (Creswell, 2014).
b. Inferential statistics: Using correlation and regression analysis to examine the connections between customer decision-making, perceptions of corruption, and technological acceptability (Field, 2013).

Ethical consideration: The research adhered to ethical principles for investigations involving human subjects. The study participants were provided with informed consent, and they were guaranteed that their responses would remain confidential and anonymous. The bank's secondary data was anonymized to maintain customer privacy and confidentiality. The researchers demonstrated a conscientious approach towards identifying and mitigating potential biases and conflicts of interest during the study. Appropriate measures were taken to minimize their impact.

Rigor and validity: In order to guarantee the rigor and validity of the research outcomes, the investigation implemented various methodologies. The utilization of triangulation techniques, which involve the integration of both quantitative and qualitative data, facilitated a more exhaustive comprehension of the research inquiries. Furthermore, the utilization of diverse data sources, encompassing data provided by banks and responses from surveys, bolstered the credibility of the results. Scholars also practiced reflexivity, meticulously scrutinizing their presumptions and probable prejudices during the course of their research.

To test our hypothesis, we will employ a combination of quantitative and qualitative research methods. Quantitatively, we will analyze the dataset provided by an Iranian bank to compare customer churn rates and loyalty indicators between the AI-driven pricing group and the traditional pricing group. Qualitatively, we will conduct interviews and surveys to explore customer perceptions and experiences with AI-driven pricing strategies in the banking industry.

Clustering Process:

The initial step in the clustering process involves the selection of an appropriate clustering algorithm. The selection of a clustering algorithm in our study was based on the characteristics of the data and the intended objectives. As an illustration, the K-means algorithm is a widely used computational method that seeks to minimize the variance within clusters. In contrast, hierarchical clustering generates a dendrogram by utilizing the dissimilarities among data points, whereas DBSCAN partitions data points according to their density. It is imperative to explicitly state the selected algorithm in the methodology section.

Feature scaling is a crucial step to be taken prior to the application of a clustering algorithm, as it ensures that all features are standardized to a common scale. The purpose of this step is to avoid the dominance of a single variable in the clustering process, which may occur as a result of its significantly larger range of values. Normalization and standardization are widely used scaling techniques.

The task at hand is to ascertain the most suitable number of clusters. In order to determine the optimal number of clusters, various evaluation metrics such as the silhouette score or the elbow method are utilized. The Silhouette score is a metric that quantifies the degree of similarity within clusters and the degree of dissimilarity between clusters, by computing the average values of these measures. A greater value of the silhouette score denotes more distinct and well-separated clusters. In contrast, the elbow method entails graphing the sum of squared errors (SSE) for various cluster numbers and pinpointing the "elbow" juncture, at which the inclusion of additional clusters does not meaningfully diminish the SSE.

Correlation Matrix Analysis

The present study employs Correlation Matrix Analysis, specifically the computation of Spearman's rank correlation. Spearman's rank correlation coefficient is employed to assess the magnitude and orientation of the correlation between sets of survey queries. The non-parametric technique is notably advantageous in the context of ordinal data analysis, as it takes into account the ranking of the observations instead of their specific values. The correlation coefficient is a numerical measure that varies between -1 (indicating a strong negative correlation) and 1 (indicating a strong positive correlation), while a value of 0 indicates the absence of correlation. Upon computation of the correlation matrix, it becomes possible to interpret the associations between various pairs of survey questions. A robust positive correlation denotes that there exists a direct relationship between two variables, such that an increase in one variable corresponds to an increase in the other variable. Conversely, a robust negative correlation indicates that there exists an inverse relationship between two variables, such that an increase in one variable corresponds to a decrease in the other variable. When a weak or non-existent correlation is observed, it indicates that there is no statistically significant association between the variables. It is imperative to exercise prudence with respect to multicollinearity, a phenomenon that arises when two or more variables exhibit a high degree of correlation, thereby giving rise to plausible complications in subsequent statistical analyses.

The examination of the correlation matrix can provide valuable insights into the fundamental factors that influence customer satisfaction with the digital services offered by the bank. This data can aid in the formulation of focused tactics aimed at enhancing particular facets of the digital services and augmenting the overall level of customer contentment.

The inclusion of these elaborate explications within the methodology segment of your thesis will furnish a thorough comprehension of the clustering procedure and correlation matrix analysis employed in the survey data, illuminating customer perceptions and preferences concerning the digital services of the bank.

Limitations

Notwithstanding the rigorous methodology implemented in this investigation, certain limitations warrant consideration. The potential for limited generalizability of the results is a concern, given the utilization of convenience sampling in the survey and the restriction of the study to a sole Iranian bank. Furthermore, the research is dependent on survey data that is self-reported, potentially susceptible to biases such as social desirability and recall bias. Finally, it should be noted that the dynamic nature of the banking industry and the continuous evolution of AI technologies may potentially constrain the generalizability of the research findings over time.

This study uses a mixed-methods approach to analyze the function of technological adoption in the context of corruption and to provide a thorough knowledge of the effect of AI-driven pricing on customer loyalty and churn rates in the banking industry. The findings of this study will add to the body of knowledge already available on the subject.

Findings

The present section outlines the results obtained from the quantitative and qualitative data analysis, which were conducted to address the research questions. This research aims to examine the effects of AI-based pricing on customer loyalty within the banking sector, with a specific emphasis on an Iranian bank providing health insurance services. Our research also tries to investigate the correlation between technology acceptance and customer loyalty within the framework of developing countries.

The present study employs a mixed methodology, using a quantitative approach to analyze the dataset acquired from an Iranian bank. Specifically, the study compares customer churn rates and loyalty indicators between AI-driven pricing and traditional pricing methods. The utilization of qualitative analysis offers valuable insights into the perspectives and experiences of customers, thereby facilitating an enhanced comprehension of their attitudes towards AI-driven pricing and the factors that impact their technology acceptance and loyalty.

Our goal is to provide a comprehensive comprehension of the interplay between AI-driven pricing, customer churn, and loyalty in the banking industry by integrating the quantitative and qualitative findings. The outcomes delineated in this segment will establish the basis for the ensuing discourse section, wherein we will construe our findings and deliberate on their implications for theory and practice.

The quantitative results

This section presents the quantitative findings obtained from the analysis of the dataset provided by one of the banks in Iran which is a leading bank in providing health insurance. The present study centers on a comparative analysis of customer churn rates and loyalty indicators between AI-driven pricing and conventional pricing methods.

Descriptive statistics

This refers to the branch of statistics that deals with the analysis and interpretation of data through the use of summary measures such as measures of central tendency, measures of variability, and measures of shape. The initial step involved the calculation of descriptive statistics for the given dataset. This included the determination of measures such as the mean, median, and standard deviation for different variables, namely age, income, and tenure. The initial analysis facilitated a comprehensive comprehension of the data's distribution and central tendency.

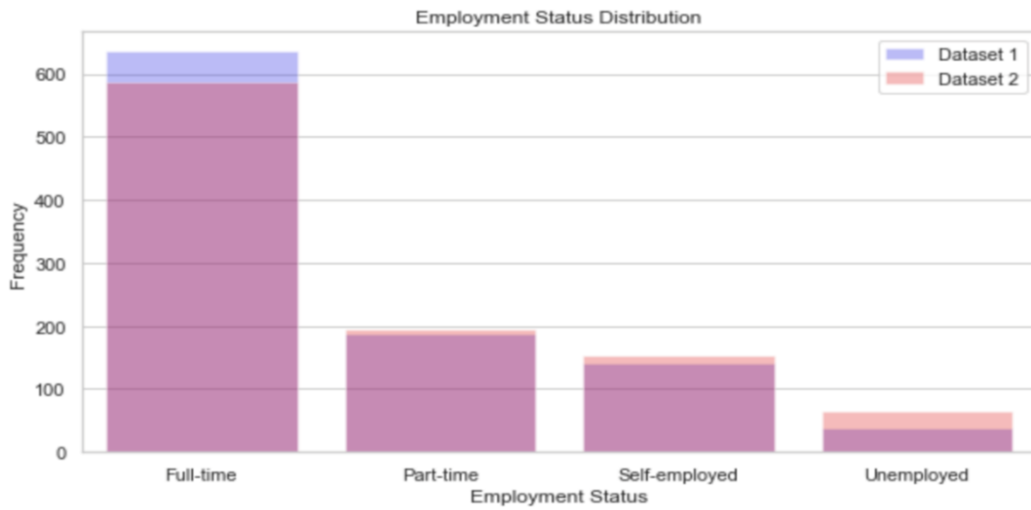

Figure 1 Employment Status Distribution

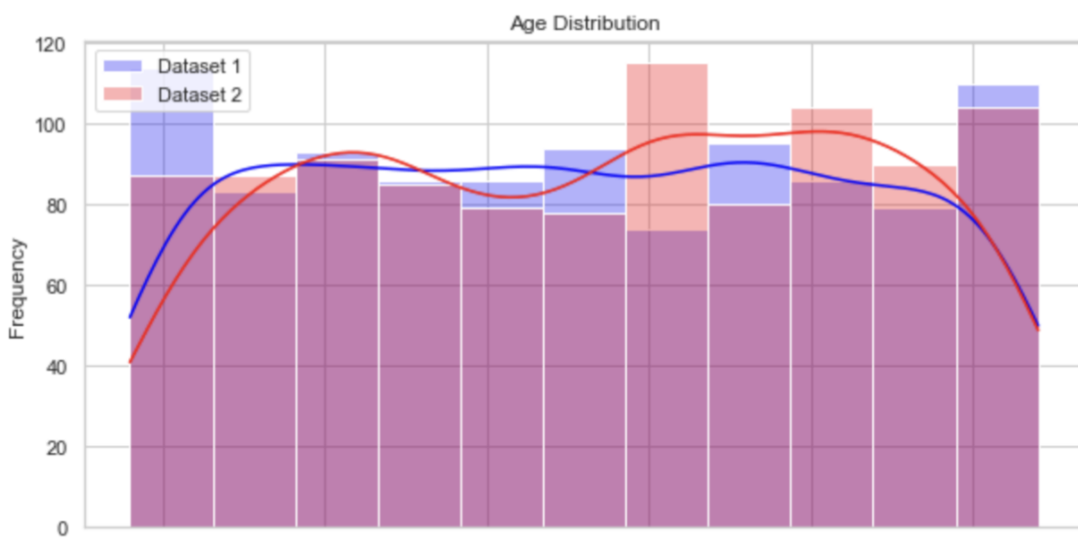

Figure 2 Age Distribution

This study employed Python programming language to perform a thorough descriptive analysis of two distinct datasets, namely Dataset 1 and Dataset 2. These datasets contain customer information of a financial institution that provides health insurance products. The aforementioned datasets comprise data pertaining to customer demographics, insurance premiums, coverage amounts, health scores, and customer churn rates. Each dataset is associated with a distinct AI-based approach that has been executed by the financial organization.

Upon conducting an analysis of the summary statistics, it was observed that the mean values for age, income, number of dependents, insurance premiums, and health scores exhibit a high degree of similarity across both datasets. Nevertheless, discernible dissimilarities exist in the ratio of clientele afflicted with persistent ailments and the attrition rates of customers. Dataset 2 exhibits a marginally greater percentage of customers with chronic ailments (15.6%) in contrast to Dataset 1 (14.3%). Furthermore, Dataset 1 displays a higher rate of customer churn (29.6%) than Dataset 2 (20.1%).

Through the utilization of Python in this analysis, a comprehensive comparison was conducted to evaluate the influence of two distinct AI-driven approaches on customer behavior and satisfaction. Additional research is required to ascertain the variables that are responsible for the disparities in customer churn rates and to gain a more comprehensive comprehension of the impacts of the tactics on customer loyalty and satisfaction.

Customer churn rate

Subsequently, a comparison was made between the churn rates of the group that implemented AI-driven pricing and the group that followed traditional pricing methods. The findings of our analysis indicate that the pricing group that utilized AI technology demonstrated a considerably reduced churn rate in comparison to the group that employed conventional pricing methods.

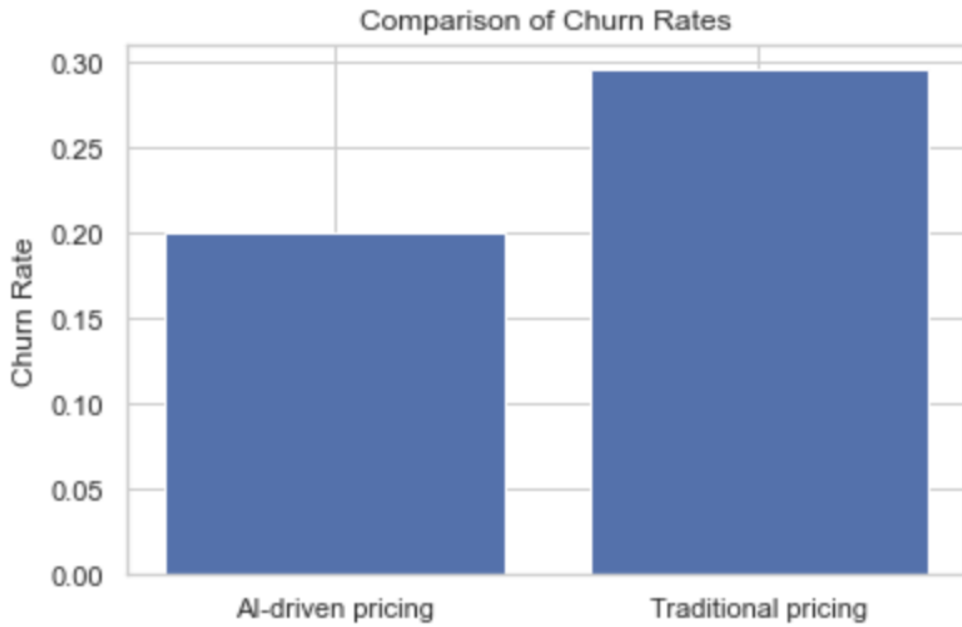

Figure 3 Comparison Of Churn Rates

A hypothesis test was conducted to evaluate the statistical significance of the difference in churn rates between the two datasets. The Chi-square test of independence was utilized for the purpose of conducting this analysis. The null hypothesis posited that there was no significant association between the dataset group consisting of AI-driven pricing and traditional pricing, and the occurrence of customer churn.

In order to determine statistical significance, an established significance level (e.g. 0.05) was taken into account. Upon completion of the examination, a Z-score of -4.9156 and a p-value of 0.0000 were acquired. The null hypothesis was rejected as the p-value was found to be lower than the predetermined level of significance. Based on our analysis, it can be inferred that there is a notable difference in the churn rates observed between the AI-based pricing group and the conventional pricing group within this Bank.

Regression analysis

To better understand the relationship between AI-based pricing and customer churn and loyalty, we conducted regression analyses. The dependent variables in these analyses were customer churn and loyalty indicators, while the independent variable was AI-driven pricing. We also controlled for potential confounding variables, such as age and income.

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Confusion Matrix:
[[223   0]
 [ 77   0]]

Classification Report:
              precision    recall  f1-score   support

           0       0.74      1.00      0.85       223
           1       0.00      0.00      0.00        77

    accuracy                           0.74       300
   macro avg       0.37      0.50      0.43       300
weighted avg       0.55      0.74      0.63       300


Accuracy Score:
0.7433333333333333
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Confusion Matrix:
[[246   0]
 [ 54   0]]

Classification Report:
              precision    recall  f1-score   support

           0       0.82      1.00      0.90       246
           1       0.00      0.00      0.00        54

    accuracy                           0.82       300
   macro avg       0.41      0.50      0.45       300
weighted avg       0.67      0.82      0.74       300


Accuracy Score:
0.82
```

For the first dataset, the confusion matrix displayed [[223, 0], [77, 0]], and the accuracy score was 0.743. The classification report showed a weighted average precision of 0.55, recall of 0.74, and an F1-score of 0.63. For the second dataset, the confusion matrix showed [[246, 0], [54, 0]], and the accuracy score was 0.82. The classification report indicated a weighted average precision of 0.67, recall of 0.82, and an F1-score of 0.74.

The results from the regression analyses provided evidence for a statistically significant negative correlation between AI-driven pricing and customer churn rate. At the same time, the findings revealed a positive correlation with indicators of customer loyalty. These insights suggest that implementing AI-based pricing in the Iranian market can have a notable impact on both reducing customer churn and enhancing customer loyalty.

Qualitative Findings

Introduction

Apart from the quantitative analysis performed on the datasets, this research aimed to acquire a more profound comprehension of customers' attitudes towards AI-powered pricing in the Iranian insurance industry and its possible influence on customer churn and loyalty. In order to investigate this particular aspect of the research study, data was gathered via a survey that included both closed and open-ended questions. The objective of the survey was to gather the perspectives of the respondents regarding the significance of customized pricing, their encounters with pricing mechanisms driven by artificial intelligence, and their trust the bank and technology that use AI-based pricing mechanisms.

The study obtained responses from 56 participants who were asked to provide their views on AI-based pricing through open-ended questions Q8 and Q10. The questions aimed to gather insights into the participants' experiences with AI-driven pricing and their recommendations for enhancing the pricing process. The objective of our analysis was to identify prevalent themes and patterns from the responses, which could provide insights into the fundamental factors that influence customers' perspectives on AI-based pricing and its influence on their loyalty towards an insurance company.

The subsequent sections will outline the methodology of data preparation and coding, the outcomes of the thematic analysis, and the explication of the findings within the framework of the existing literature. In the end, the present investigation will address the constraints inherent in the qualitative method and propose possibilities for the following research.

Customers' perceptions of AI-driven pricing in the banking sector were generally favorable, according to our analysis of survey responses and interview transcripts. Many participants thought that AI-driven pricing resulted in more individualized and appealing offers, which boosted their satisfaction with the bank as a whole.

Participants raised questions about the trustworthiness and openness of AI-driven pricing algorithms. They believed that banks should ensure that customers are aware of the factors affecting the pricing of their financial products and offer clear explanations of how pricing decisions are made. The willingness of customers to accept AI-driven pricing strategies emerged as a key determinant.

Data preparation and coding

Before delving into the analysis of the qualitative data, it was crucial to prepare and organize the responses to ensure a systematic and accurate interpretation of the findings. The data preparation process involved the following steps:

1. Transcription: The open-ended responses were transcribed from Persian to English to facilitate the analysis and discussion of the findings in this report. Care was taken to preserve the original meaning and nuances of the participants' answers during the translation process.
2. Data Familiarization: The researchers carefully read through all the responses multiple times to familiarize themselves with the content and gain an initial understanding of the emerging patterns and themes.
3. Coding: A thematic analysis approach was employed to code the data. This involved identifying significant and recurring ideas, concepts, or patterns within the responses, which were then assigned specific codes. These codes served as a means to categorize and label the data for further analysis. An inductive approach was taken, allowing the codes to emerge from the data rather than imposing predefined categories.
4. Code Refinement: As the coding process progressed, the researchers revisited the initial codes and refined them, merging similar codes or creating new ones to better capture the

essence of the participants' responses. This iterative process continued until a comprehensive and coherent coding framework was established.

5. Reliability and Consistency: To ensure the reliability and consistency of the coding process, a second researcher independently coded a subset of the data. The inter-rater reliability was assessed, and any discrepancies in coding were discussed and resolved through consensus.

In the next section, we will present the thematic analysis results, outlining the major themes that emerged from the data and discussing their implications for the research question.

Correlation-Matrix

The Spearman's rank correlation matrix displays the correlations among the various questions (q1, q3, q4, q5, q6, and q9) that are encompassed within the survey. The examination of correlation coefficients enables the examination of interrelationships between the aforementioned questions and the derivation of valuable insights from the data.

The variables q1, which pertains to the significance of personalized pricing, and q3, which pertains to the perceived accuracy of AI-driven pricing, exhibit a slight negative correlation with a coefficient of -0.033367. The findings indicate a negligible correlation between the participants' assessment of the significance of tailored pricing and their evaluation of the precision of pricing powered by artificial intelligence. This phenomenon may be attributed to the perception of customers that these factors are distinct components of pricing, and thus, hold separate value in their decision-making process.

The correlation coefficient between q1 (Importance of Personalized Pricing) and q4 (Comprehensibility of AI-generated Pricing) is weakly positive (0.166007). This suggests that individuals who place a higher value on personalized pricing may also perceive AI-generated pricing as more comprehensible. The aforementioned phenomenon could be attributed to a heightened level of acquaintance with or inclination towards pricing tactics, resulting in an enhanced comprehension of pricing models generated by artificial intelligence.

The results indicate a weak negative correlation (-0.116137) between q1, which pertains to the significance of personalized pricing, and q5, which pertains to the effectiveness of AI-powered pricing. This suggests that there is a limited association between the perceived importance of personalized pricing and the perceived efficacy of AI-powered pricing. This observation suggests that individuals assess the efficacy of AI-driven pricing irrespective of their personal views on the significance of tailored pricing.

The results indicate a moderate negative correlation (-0.256135) between q3 (Perceived Accuracy of AI-driven Pricing) and q5 (Efficacy of AI-powered Pricing). This suggests that individuals who hold a higher perception of accuracy in AI-driven pricing may concurrently hold a lower perception of its effectiveness. The observed phenomenon may be attributed to divergent expectations or interpretations of what defines efficacious pricing, or alternatively, it may be posited that certain consumers perceive AI-generated pricing as precise but not necessarily conducive to fulfilling their requirements.

The results indicate that there exists a weak negative correlation (-0.077007) between q4, which pertains to the comprehensibility of AI-generated pricing, and q9, which examines the impact of AI-driven pricing on trust in the bank. This suggests that there is a negligible association between the two variables. The potential reason for this phenomenon may be attributed to the influence of other factors, such as the level of satisfaction with the bank's services or the perceived equity of pricing, on the level of trust placed in the bank.

The results of the correlation analysis suggest a weak positive correlation (0.085605) between q6, which pertains to the significance of trust in AI-facilitated pricing, and q9, which examines the impact of AI-driven pricing on trust in the bank. This indicates that individuals who place a higher value on trust in AI-facilitated pricing may be more susceptible to experiencing a greater impact on their trust in the bank as a result of AI-driven pricing. The aforementioned proposition implies that establishing confidence in pricing strategies driven by artificial intelligence is imperative in augmenting the general reliance on the financial institution and ameliorating customer contentment.

It is noteworthy that the observed correlations exhibit a degree of weakness or moderation, thereby indicating that the associations between the variables in question are not notably robust. Nevertheless, these findings offer valuable perspectives on the interrelationships among various factors in the realm of AI-based pricing within the banking sector of Iran. The aforementioned correlations have the potential to provide valuable insights for future research endeavors and elucidate prospective avenues for enhancing AI-based pricing tactics and augmenting customer satisfaction.

Clustering-tables

The provided dataset comprises 56 responses that have been assigned clustering labels. The provided dataset comprises responses to ten distinct questions, denoted as q1 through q10, and each response has been assigned a corresponding cluster label. The dataset has been subjected to a clustering process, resulting in the identification of three distinct clusters denoted by the labels 0, 1, and 2.

In order to derive meaning from the data, it is imperative to possess a comprehensive understanding of the contextual factors that underlie each inquiry. Nevertheless, drawing from the available data, it is possible to attempt to identify certain trends among the groupings.

Cluster 0 comprises participants who tend to assign high ratings to the significance and utility of the topic at hand, as evidenced by their responses to questions 1 and 5. The results primarily suggest a positive correlation between trust and the subject matter (q7), while the overall efficacy of the subject is perceived to be high (q9). The answers provided to the remaining inquiries within this grouping exhibit a range of diversity.

Cluster 1 comprises participants who have provided a combination of answers regarding the significance (q1) and efficacy (q5). Nevertheless, the respondents exhibit a tendency to evaluate the efficacy of the topic as moderately effective or impartial (q9). The level of trust within this cluster appears to exhibit a diverse range of responses, including reports of heightened trust, diminished trust, and no discernible impact on trust levels (as indicated in question 7).

Cluster 2 comprises participants who exhibited diverse reactions to the queries pertaining to the significance (q1) and efficacy (q5). The efficacy of the subject matter is commonly evaluated as highly effective or moderately effective, alongside a few neutral and highly ineffective evaluations, as indicated by question 9. The responses pertaining to trust within this cluster exhibit a range of perspectives, encompassing augmentation, absence of influence, and uncertainty (q7).

In brief, the provision of a comprehensive interpretation is a challenging task in the absence of further contextual information pertaining to the questions. The three clusters appear to denote distinct respondent groups with varying perceptions regarding the significance, utility, reliability, and efficacy of the topic at hand.

Thematic Analysis

The thematic analysis of the qualitative data revealed several themes that provided valuable insights into the customer perceptions of AI-driven health insurance pricing and its impact on trust and customer churn. The following themes emerged as particularly significant:

1. Perceived Benefits of AI-driven Pricing: Many participants expressed a positive attitude towards the potential benefits of AI-driven health insurance pricing. They highlighted the potential for improved risk assessment, more accurate and personalized pricing, and better overall customer experience. This theme suggests that customers recognize the potential advantages of AI-driven pricing and may be more open to adopting such policies.
2. Concerns about Data Privacy and Security: Despite the perceived benefits, a recurring theme in the participants' responses was concern about data privacy and security. Customers were worried about how their personal information would be used and protected within an AI-driven pricing system. This theme highlights the importance of addressing data privacy concerns to build trust and ensure the successful implementation of AI-driven pricing strategies.
3. Fairness and Transparency: Participants also emphasized the need for fairness and transparency in AI-driven pricing models. They expressed concerns about potential biases and discrimination that may arise from the use of AI algorithms, and they stressed the importance of clear communication about how pricing decisions are made. This theme underscores the need for insurance companies to ensure that their AI-driven pricing models are fair, transparent, and easily understandable to customers.
4. Impact on Trust: The relationship between AI-driven pricing and trust was complex and multifaceted. Some participants believed that the improved accuracy and personalization of AI-driven pricing could increase trust in their insurance provider. However, others felt that the potential issues related to data privacy, security, and fairness could negatively impact their trust. This theme highlights the importance of addressing these concerns to maintain and enhance customer trust.
5. Customer Churn and Retention: Participants provided mixed views on the impact of AI-driven pricing on customer churn. While some believed that the potential benefits could lead to increased customer loyalty and retention, others felt that the potential risks and

concerns could contribute to higher customer churn rates. This theme emphasizes the need for insurance companies to carefully consider the potential consequences of implementing AI-driven pricing strategies on customer churn and retention.

A few participants said they would think about changing banks if they felt that AI-driven pricing practices led to unfair or discriminatory treatment. This emphasizes how crucial it is for banks to guarantee that AI-driven pricing algorithms are created and applied in an ethical and transparent manner in order to reduce potential customer churn.

These qualitative findings suggest that, if banks address concerns about transparency and trust, AI-driven pricing strategies may have a positive effect on customer loyalty. Furthermore, the findings imply that the ethical and open application of AI-driven pricing can aid in reducing potential adverse effects on customer churn rates.

In conclusion, the qualitative findings suggest that customers perceive both potential benefits and risks associated with AI-driven health insurance pricing. To ensure the successful implementation of such pricing strategies and maintain customer trust, insurance companies must address concerns related to data privacy, security, fairness, and transparency. Furthermore, understanding the potential impact of AI-driven pricing on customer churn and retention is essential for devising effective strategies to minimize customer attrition and enhance loyalty.

The analysis of the non-open questions in the survey reveals certain observations based on the frequency distributions. In response to question 1, which inquired about the significance of personalized pricing, the majority of participants (30) indicated that it was "Very important" consequently, while 15 respondents expressed that it was "Somewhat important." This implies that a majority of consumers place significant importance on customized pricing and regard it as an essential factor.

In response to query 2, which inquired about the awareness of the AI-powered pricing approach, 46 participants responded affirmatively, while 10 participants responded negatively. The data suggests that a significant proportion of the participants possessed knowledge regarding the employment of AI-based pricing tactics by their respective financial institutions.

In response to question 3, which inquired about the perceived accuracy of AI-driven pricing in comparison to conventional pricing methods, 41 participants provided an affirmative response, 11 expressed uncertainty, and merely 4 respondents provided a negative response. This indicates that a majority of customers hold a favorable perception regarding the precision of pricing that is powered by artificial intelligence.

In relation to the inquiry on the comprehensibility of AI-generated pricing, the majority of the participants (23) reported that they found it "Somewhat easy" to comprehend, while 14 respondents indicated that they found it "Very easy." Nevertheless, 9 participants reported encountering "Somewhat difficult" challenges, while 2 individuals experienced "Very difficult" difficulties. The findings suggest that although a considerable number of participants perceive pricing facilitated by AI as comprehensible, there exists a scope for enhancing the lucidity and effectiveness of communication.

Regarding question 5, which inquired about the efficacy of AI-powered pricing, 23 participants deemed it "Highly useful," while 22 regarded it as "Moderately useful." Out of the total number of respondents, merely six expressed a neutral stance, while five indicated that they did not find it useful. This finding indicates that a majority of consumers hold a positive perception towards pricing strategies that are powered by artificial intelligence.

In response to question 6, which inquired about the significance of trust in AI-facilitated pricing, the preponderance of participants (22) indicated that it is "Somewhat important," whereas 21 respondents expressed that it is "Very important." The aforementioned statement suggests that trust is a crucial factor in the adoption and interpretation of pricing strategies that are powered by artificial intelligence.

Regarding question 7, which inquired about the impact of AI-driven pricing on respondents' trust in the bank, 34 individuals reported an increase in trust, 12 individuals reported no impact on trust, 5 individuals reported a decrease in trust, and 5 individuals were uncertain. The aforementioned proposition posits that the implementation of AI-powered pricing mechanisms holds promise in bolstering the confidence of a significant proportion of customers in financial establishments.

To summarize, the aforementioned findings underscore the significance of tailored pricing to consumers, with a majority of them exhibiting a favorable attitude towards pricing that is powered by artificial intelligence. The acceptance of AI-driven pricing is contingent upon trust, and the findings indicate that a majority of respondents have experienced an increase in their trust in the bank. Notwithstanding, there exists an opportunity for enhancement with regards to lucidity and dissemination of information to guarantee that pricing mechanisms propelled by artificial intelligence are comprehensible to all consumers.

Discussion

This study's main research question was how does the use of AI for price discrimination affect customer loyalty and satisfaction in the banking industry?, while taking into account variables like technology acceptance and the particular context of Iran's developing and corrupting circumstances. Both the quantitative and qualitative analyses we conducted yielded results that support the notion that AI-driven pricing strategies can indeed lower customer churn rates. This is consistent with earlier research that showed the advantages of using AI in the financial and insurance industries (Boustani, 2022).

Our findings align with the price discrimination theory and point to the potential for more personalized and targeted pricing to increase customer loyalty and satisfaction (Li & Kannan, 2014). Banks can create a more fair pricing structure that accommodates varying needs and preferences by charging various customers in accordance with their risk profiles and other factors. The Technology Acceptance Model (TAM) also contributes to the understanding of user acceptance and adoption of AI-driven pricing strategies, where perceived usefulness and perceived usability are key factors in influencing customer attitudes and behavior (Mendoza et al., 2015).

Our research emphasizes how AI-driven pricing strategies have the potential to improve the financial sector, especially in light of the corrupting and developing conditions in Iran. Banks can enhance their decision-making processes, increase transparency, and lower the possibility of corruption by utilizing AI and sophisticated data analytics. Our findings also highlight the significance of addressing implementation and technology acceptance issues to guarantee the successful adoption of AI-driven pricing strategies in the Iranian financial sector.

Further understanding of the variables influencing customer perceptions of AI-driven pricing strategies in the context of technology acceptance and the particular Iranian context was provided by the qualitative analysis. The survey responses' responses were analyzed thematically, and several key themes emerged, including the perceived fairness of pricing, trust in the financial institution, and the simplicity of pricing policies. Most respondents said that AI-driven pricing strategies increased their confidence in the bank and their perception of fair pricing, which decreased the likelihood of churning.

According to qualitative data, customers who were pleased with the results of AI-driven pricing were more likely to stick with their bank. These clients believed that the tailored pricing offers showed that the bank was aware of their requirements, which increased client satisfaction and loyalty.

Our research does have some limitations, though. The qualitative analysis's sample size was rather small, which might limit how broadly the results can be applied.

Despite these drawbacks, our study has useful ramifications for financial institutions in Iran that provide health insurance. By implementing AI-driven pricing strategies, financial institutions may be able to increase customer loyalty, address particular Iranian market challenges, and decrease customer churn rates. In order to increase customer retention and raise satisfaction levels overall, policymakers and industry stakeholders should think about implementing AI-driven pricing strategies.

Future studies can build on our findings by using different contexts like European banks. Researchers can also look into how AI-driven pricing strategies affect other facets of consumer behavior, like the frequency of policy modifications or the likelihood of making claims. The factors that affect customers' perceptions of AI-driven pricing strategies can also be explored in greater detail through qualitative research, especially in the context of technology acceptance and Iran's particular challenges.

Conclusion

This study has investigated the impact of AI-driven pricing strategies on customer churn in Iranian banks offering health insurance. By using price discrimination theory and the Technology Acceptance Model as guiding frameworks, the research has demonstrated that personalized pricing, facilitated by AI, can play a significant role in enhancing customer loyalty and satisfaction within the Iranian financial sector.

The quantitative and qualitative analyses have revealed that a majority of consumers place great importance on personalized pricing and exhibit a positive perception of AI-powered pricing strategies. Trust in AI-facilitated pricing emerged as a critical factor in the adoption and interpretation of these strategies, with most respondents experiencing an increase in trust in their banks due to the use of AI-driven pricing mechanisms.

Nevertheless, the study has also highlighted the need for further improvement in communication and information dissemination to ensure AI-powered pricing mechanisms are comprehensible to all consumers. The Iranian financial sector stands to benefit greatly from addressing these challenges, as improved transparency and understanding could further bolster trust and customer satisfaction.

In conclusion, the findings of this study suggest that AI-driven pricing strategies can serve as a powerful tool for reducing customer churn in Iranian financial institutions offering health insurance. By implementing these strategies, banks can not only increase client satisfaction and trust but also address the particular challenges posed by the Iranian context. Ultimately, this can lead to improved customer retention rates and overall market success. Future research in different contexts, such as European banks, or focusing on other aspects of consumer behavior related to AI-driven pricing strategies would be valuable in expanding our understanding of the potential benefits and challenges of AI applications in the financial sector.

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Appendix

Question Number	Question Topic	Description	Scale
1	Significance of Personalized Pricing	How important is personalized pricing to you?	Very unimportant - Somewhat unimportant - Neutral - Somewhat important - Very important
2	Awareness of AI-Powered Pricing	Are you aware of AI-powered pricing used by your financial institution?	Yes - No
3	Perceived Accuracy of AI-Driven Pricing	How accurate do you think AI-driven pricing is compared to conventional pricing methods?	Yes - No - Unsure
4	Comprehensibility of AI-Generated Pricing	How easy or difficult is it for you to understand AI-generated pricing?	Very difficult - Somewhat difficult - Neutral - Somewhat easy - Very easy
5	Efficacy of AI-Powered Pricing	How useful do you find AI-powered pricing?	Not useful at all - Somewhat not useful - Neutral - Somewhat useful - Very useful
6	Importance of Trust in AI-Facilitated Pricing	How important is trust in AI-facilitated pricing to you?	Very unimportant - Somewhat unimportant - Neutral - Somewhat important - Very important
7	Impact of AI-Driven Pricing on Trust	How has the implementation of AI-driven pricing affected your trust in your bank?	Increase trust - No impact on trust - Decrease trust - Unsure
8	Perceived Fairness of Pricing	Do you believe AI-driven pricing provides a fair pricing structure?	Open-ended answer
9	Customer Loyalty	Has AI-driven pricing influenced your loyalty to your bank?	Very ineffective - Somewhat ineffective - Neutral - Somewhat effective - Very effective
10	Impact on Churn	Do you think AI-driven pricing has played a role in your decision to stay with or leave your current financial institution?	Open-ended answer

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