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Integrating predictive analytics into health insurance operations: A framework for cycle time optimization

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Abstract

The escalating complexity of health insurance processes has led to the need to find new solutions to realize the efficiency, cost-reduction, and service delivery. The analytics technique known as predictive analytics is a statistical model based analytics using machine learning to predict the outcome and it can deliver gigantic potential in the area of maximizing the time in the operation of the insurance business to include the underwriting processes, claims management processes, and fraud detection processes. The review article investigates the way predictive analytics can be integrated into health insurance operation and proposes a template on the optimization of the cycle time. Based on the synthesis of the recent literature, the paper identifies a collection of core aspects of integration, which include data consolidation, model development, workflow embedding, feedback-driven learning, and ethical governance. It highlights the importance of predictive systems in helping the insurers to automate decision making, concentrate on low-risk claims, detect fraudulent activity, and customize customer interaction. The given model is aimed at the cycle of constant improvement with the help of monitoring performance and open governance which will ensure the long-term enhancement of the operational efficiency and compliance with the laws. Additionally, the article discusses the issues related to data privacy, algorithm bias, and interpretability and provides the ethical and technical solutions to eliminate the risks. The future research directions are to bring artificial intelligence, blockchain, and Internet of Things (IoT) into the picture to obtain more interoperability, transparency, and real-time flexibility. Overall, this paper has demonstrated that predictive analytics is not only a groundbreaking technology, but also a wonderful strategic enabler to efficiency, accountability and innovation in the health insurance sector.

Keywords: Predictive Analytics; Health Insurance; Cycle Time Optimization; Machine Learning; Data Governance

1. Introduction

Health insurance companies are increasingly feeling the strain to be more efficient in operations and at the same time have high standards of accuracy, compliance and customer satisfaction. In that regard, predictive analytics which is the application of data, statistical algorithms and machine learning methods to determine the probability of future results based on preceding information has become a revolutionary in streamlining health insurance processes [1]. Cycle time is one of the most important performance indicators in this industry because it is defined as the time between the start and end of a process including claim adjudication, underwriting or even issuing a policy. Long cycle times do not only slow down the reimbursements and raise the administrative expenses but also affect the customer satisfaction and trust negatively. The traditional operations of health insurance has been dependent on rule-based systems and manual interventions which have been inefficient and resulted in redundancies. Predictive analytics provides an alternative based on data, which predicts the amount of claims, detects any fraud and estimates customer risk more accurately [2]. Carrying out the models of forecasting throughout the operating cycle, the insurers are able to streamline the decision-making process, minimize human mistakes, and improve turnaround time. As an example, predictive claim scoring

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models may also determine the claim validity in real time and assign low-risk claims to fast-track processing and route high-risk claims to additional assessment.

Resource optimization is also made possible through the incorporation of predictive analytics into the functioning of operations, as insurers will be able to foresee any changes in workloads and distribute human and technological resources more efficiently. Additionally, the predictive knowledge will be able to enable an individual customer-specific engagement where the insurers will be able to tailor the premiums, develop preventive health programs, and increase retention rates [3]. The predictive analytics usage in health insurance is not completely adopted because of obstacles including data silos, model interpretability, and privacy issues, regardless of its potential. It is thus important to develop a systematic structure of integrating predictive analytics in the current health insurance system. This framework should deal with data governance, interoperability, and ongoing model review to deliver sustainable operational advantages [4]. The purpose of this paper is to conduct a review of the literature that exists on the topic of predictive analytics applications in health insurance, suggest a detailed framework of cycle time optimization, and the enablers and barriers that govern its application. In so doing, it adds to the expanding literature on data-driven change in the operations of health insurance.

2. Background

The rising level of travesty of healthcare systems has enhanced the speed at which predictive analytics are integrated into the operations of health insurance. Predictive analytics uses big amounts of both structured and unstructured data to provide insights to facilitate both the strategic and operational decisions. Forecasting the outcome of claims, fraud detection, and estimating the risk of a customer in health insurance have the potential to greatly simplify the administrative procedure and maximize the cycle times [5]. This shift between the reactive management and predictive management allows the insurers to take the initiative and limit inefficiencies in claim adjudication and premium pricing, as well as, member engagement.

The operations of health insurance in the past were based on manual reviews and business rules. These methods were time consuming and they tended not to arrive at complex relations in the data. Predictive analytics uses machine learning and statistical modeling to add an adaptive layer, which adapts as additional data is made available. Indicatively, the regression models, decision trees, and ensemble learning are becoming more popular with insurers to forecast claim probability and probability of fraud and enhance operational decision speed and accuracy [6]. Incorporating prediction systems into the claims lifecycle, insurers are able to automatically categorize claims based on risk level, detect anomalies and set workflow priorities that imply shorter cycle times.

Another major area of application is underwriting and risk assessment. The predictive analytics will help the insurance companies to maximize the risk scoring models by combining behavioral, clinical and demographic variables. The present health insurers do not just utilize the tables given by the actuaries, they have predictive risk models that continue to update with incoming member data. This is an actual time risk adjustment not only does it make the underwriting quick but also improves on the accuracy of the premiums and equity. Studies show that this form of integration can save up to 40 per cent of time on the underwriting process yet meet the regulatory demands [7]. In addition, predictive analytics enhances the overall population health management performance by targeting high-risk cohorts at an early stage so that the insurers can design preventive intervention programs that will reduce the cost of claims in the long-term. Predictive modeling can also be applied in the detection and prevention of fraud which is a challenge in the operation of health insurance. Pseudo statements increase the administrative costs and lengthen the process. To be able to reduce the financial loss and delay in the processing, predictive systems that detect anomaly can be made to identify suspicious claims prior to payment authorisation. To illustrate, machine learning models such as neural networks and random forests have been implemented to identify deviant claim behavior and anomalies of provider billing [8]. The inclusion of these systems into the workflow will make sure that the fraudulent claims are identified at earlier stages of the working process, which will directly lead to the reduction in the duration and efficiency of the claiming process.

Besides, customer relationship management (CRM) and customer retention of health insurance depends on predictive analytics. Predictive analytics provide an opportunity to predict the likelihood of churn and recommend tailored outreach by examining the behavior of policyholders, payment histories, and patterns of service use. This does not only improve customer experience but also indirectly increases operational optimization a lower number of dropped customers means a lower cost of onboarding and more predictable revenue cycles. Predictive insights can also help insurers to recommend preventive health services to improve the health outcomes and operational efficiency.

Although there exist advantages, there are a number of challenges that are involved in prediction analytics use in health insurance. The problem of data fragmentation is also a significant hindrance; the majority of insurers have various systems to handle claims, provider network and customer data, and it is hard to unify. In addition to that, the ethical use of predictive models, namely, their deployment in data privacy and bias particulars, is to be strictly controlled. The predictive models hence need to be decipherable and clear particularly when it is utilized in decision-making processes that directly affect customers. The second challenge is the preparation of the work force: to integrate analytics well, inter-disciplinary teams consisting of actuarial, data science, and operational experience have to be formed. The mass of literature that has been accumulated is pointing to the fact that predictive analytics is not a mere technological enhancement, but paradigm shift in how health insurance is managed. The move towards predictive and prescriptive decision making enables insurers to come up with learning systems that continually enhance the operations. This makes predictive analytics a core component on which cycle time optimization can be performed, with the operational processes dynamically changed according to data feed-back at real-time.

3. Literature review

Predictive analytics is emerging as a staple of digital transformation in healthcare and insurance industry. Within the last ten years, there is an increasing body of research on its role in increasing operational efficiency, decision-making, and managing cycle-time. Some of the main areas of application as mentioned in the literature include claims management, underwriting, fraud detection and customer retention. When some studies are based on technicalities of predictive modeling, the number of those studies that discuss its application to end-to-end operations in health insurance is even smaller, which is a major gap that this review aims to fill.

Predictive analytics help the insurers to automate the triage, fast-track the low-risk claims in claims management and to allocate resources more effectively. Predictive scorecard systems are based on enormous historical data to make predictions on the validity of claims and early detect possible mistakes during the process [9]. These systems utilize logistic regression, decision trees and gradient boosting algorithms to categorize claims based on risk level. Insurers can save the total processing time that can be spent on administrative expenses because it is possible to give priority to clean claims and forward complex claims to be reviewed manually. In a study, Zhou and Lin (2022) showed that predictive claim scoring decreased the average time of claim cycle by 35 percent in large U.S. insurance companies by simplifying decision points and reducing unnecessary approvals [9]. There is also the rise of predictive analytics in detecting fraud. False claims and inflated billing are other forms of health insurance fraud that have been the greatest defaulters of inefficiency. The latest analytics systems are using deep learning, clustering and anomaly detection algorithms to identify the existence of fraud patterns in near real time [10]. Such systems do not only enhance accuracy, but also minimize the duration of the cycles by minimizing the amount of manual investigations needed. Predictive fraud analytics has therefore become an essential component of operational optimization and it seamlessly fits in the claims adjudication processes and compliance procedures.

Predictive analytics can help to increase the accuracy of assessment of the risk profile of policyholders in the field of underwriting and risk assessment. Research has shown that behavioral and clinical data can be used in predictive underwriting models that enable the underwriter to save a lot of time underwriting and, at the same time, comply [11]. In addition, combining machine learning and actuarial technique will produce a dynamic risk scoring environment that improves with the increased availability of data. This contains the flexibility enabling the insurers to become sensitive to the new risks in the market which will ultimately be efficient and translucent in operations and price. Predictive analytics are also applied in customer relationship management (CRM) and retention strategies besides risk and claims management. The insurers use the churn prediction models to single out potentially lapsing or switching customers. This type of model can be applied to implement focused retention campaigns through analyzing the customer demographics, claim history and involvement pattern, and increasing their customer satisfaction and reducing the acquisition costs [12]. It is an oblique mechanism of optimizing cycle time in that it balances customer databases, besides reducing administrative costs of policy renewals. In spite of such developments that have occurred, there have been difficulties in the operationalization of predictive analytics models that remain within the literature. The problem of integration of the data still remains; the insurers are likely to have multiple legacy systems that do not support the flow of the data between departments. The other problems are connected with the interpretation of the models which is one of the most important conditions of regulatory compliance and customer disclosure. Predictive models are also supposed to be comprehensible and testable especially when they are used to make high-stakes decisions such as denial of claims or pricing of policies. Furthermore, it is stressed that the need to introduce effective data governance systems exists. that would help to protect patient and policyholder data in accordance with HIPAA and GDPR regulations (as cited in Kim et al., 2019). The literature highlights that although predictive analytics have proven to be successful in streamlining certain aspects of the insurance business, a lack of a comprehensive integration platform restricts its

ability to transform. The following part of the paper suggests an elaborate design of how predictive analytics can be introduced into the business of health insurance to optimize the end-to-end cycle time (Table 1).

Table 1 Comparison of predictive analytics applications in health insurance

Application Area	Predictive Model Used	Operational Benefit
Claims Management	Logistic regression, gradient boosting	35% reduction in cycle time through automated claim routing
Fraud Detection	Deep learning, anomaly detection	40% improvement in fraud detection accuracy and faster processing
Underwriting	Random forests, ensemble learning	30–40% reduction in underwriting turnaround time
Customer Retention	Neural networks, churn models	25% improvement in retention rate and reduced renewal delays

4. Framework development

The predictive analytics implemented into health insurance operations need a well-defined framework that network data inputs, analytical models, and operational processes into a continuous improvement process. An effective framework will assure that the predictive models are not viewed as standsalone technical solutions instead they are integrated into the core operations of the insurers to enable quantitative efficiency of operations, especially improvement in the cycle time. The framework presented in this paper is based on existing theories of analytical and process optimization, which are altered to the requirements of the health insurance setting with a complex data environment and regulatory limitations. The framework starts at the base with the data acquisition and integration, which entails the conglomeration of both internal and external sources of data into a single data repository. Health insurance activities rely on several sources of data that include claims, electronic health records (EHRs), customer demographics, and provider data. Such a combination of datasets will enable taking a holistic view of the policyholder journey and developing more accurate predictive models. The latest study aimed at understanding how real time data integration with cloud based infrastructures would enhance responsiveness and speed of decision making on the model [13]. Such kind of integration will provide the data to be better available and even will enable the insurers to perform predictive analytics on the scale without compromising the data security and compliance. The second phase in the structure is the model creation and verification, the advanced machine learning and statistical tools will be utilized to predict specific outcomes e.g. the time length of the claims, the possibilities of committing fraud or the level of risk. Ensemble methods such as random forests and gradient boosting have likewise been discovered to be more predictively precise than more customary regression techniques and are particularly precise when dealing with large, heterogenous insurance data [14]. Model validation is a mandatory procedure that ensures the predictive reliability prior to field implementation. The retraining mechanisms are continuous so that the models will be accurate to the varying data distributions as the course of time changes. Such loop system facilitates the system to be trained on new patterns and this is in conformity with the notions of adaptive learning and continuous process improvement.

Predictive models are deployed to operation workflow layer after being tested and they directly interface with business processes such as a claims adjudication process underwriting and fraud detection. Such integration transforms predictive knowledge into action decision in real time. An example is that the claims can be automatically grouped into fast-track, moderate-risk, and high-risk groups using claim scoring algorithms, and therefore the system can easily allocate processing resources and minimize time delays [15]. In the same line, predictive underwriting model can contain real-time risk-related measurements which can be actualized during the issuance of the policy thus making it possible to charge dynamically and accelerate the process of issuing the policy. Integration of the predictive deliverables into the workflow management systems ensure that there are data-driven operational decisions that are continuously optimized.The feedback loop of performance monitoring is a vital part of the framework and completes the analytical cycle. This loop takes in performance data, in the form of the claim cycle time, fraud detection rate, and customer satisfaction, and repeats it into the system to adjust model parameters and increase the overall process efficiency. The provision of performance dashboards and visualization improve transparency, which enables managers to measure the actual effect of predictive interventions in real-time. It has been found that the companies that develop feedback-based predictive systems can enjoy a long-term performance increase, and a quantifiable decrease in processing delays and error rates [16].

Lastly, the structure includes a governance and ethical control layer, which source-checks the regulatory requirements and ethics. Health insurance predictive analytics often involve personal and health-related information which is sensitive and it is therefore important to adopt stringent data governance policies. These involve model decision-making transparency, algorithmic output fairness, and data handling practice accountability. Regular audits, explainability protocols, and stakeholder review procedures should be among the governance structures to achieve an ethical fit and compliance with regulations. Integration of ethics is both a legal requirement, but also a component of trust, which is also key to customers accepting predictive systems.

The conceptual diagram of the proposed structure is presented in Figure 1 (discussed in this section). It comprises of five interrelated elements such as data integration, model development, operational deployment, performance feedback and governance. The cyclic character of the framework is an ever-improving model that is updated with the input of data and feedback concerning the operation. Such cyclical integration will make predictive analytics a natural component of organizational learning and processes optimization.

Overall, this framework provides a structure to integrate predictive analytics into the work of health insurance. Through optimizing the cycle time by aligning data, models and workflows aligned by a feedback-based governance structure, insurers can strike a balance between compliance, accuracy and transparency. The framework preconditions the integration with the upcoming technologies and blockchain could be used to improve the security and process automation.

5. Implementation strategies

The implementation of the predictive analytics into the health insurance business should take a systematic method where the technological capabilities, process reengineering, and organizational readiness are balanced. The conceptual framework offered by the prescription is the basis of the real-life applications even though they are anchored on the ways in which the predictive systems are integrated within the core operations which are, claims management, underwriting, fraud detection and customer engagement. Implementation aims not only to have the implementation of predictive models in place but coded into decision-making processes that constantly optimize the process to cut the cycle time of all operation levels.

Predictive analytics is used in the claims processing field to automize the process of triaging claims and accelerating low-risk claims. The traditional claims processing has several sequential steps, i.e., submission, verification, adjudication, and approval, which all create possible bottlenecks. This is simplified with the help of predictive models that are based on incoming data on claims and a probability score is attributed to each case. Claims that are of low fraud probability with a high completeness rating are automatically approved and those that are outliers are sent through to a second review. Rajan and Khatri (2021) assert that predictive claim scoring has cut claim processing in large insurers by up to 45 per cent due to enhanced task prioritization and real-time fraud detection [17]. This automation improves the agility of operations and ensures accuracy and compliance with the regulations.

Predictive models are combined in the process of underwriting to facilitate the rapidity of risk evaluation and policy decision. Rather than adopting purely the actuarial formula, predictive underwriting makes use of dynamic data sources, including health behavior measures, telemedicine histories, and credit-driven risk measures. This data stream can be used to assess the risk of the applicants in real-time and thus the insurers can issue policy more quickly and accurately. The predictive analytics applied in underwriting have been proven to minimize the human touch and to minimize the average time taken to issue a policy by approximately 30 percent [18]. This change would need close coordination of data scientists, actuaries and underwriters in order to make sure the predictive models are in line with the business rules and regulation provisions.

The other key area of implementation is detection of fraud, it is a dual role where predictive systems are used in both detection and prevention of fraud. Fraud in healthcare insurance is a widespread problem that makes the administration of the procedures expensive and prolongs the duration of receiving claims. Predictive analytics systems are based on unsupervised learning and clustering algorithms and neural networks, applied to detect anomalous claims patterns that indicate fraud. As the insurers can include such systems into the claims workflows, they will be able to identify the fraudulent behavior earlier in the process, which will lead to fewer cases where their investigations will be conducted retrospectively. One of the recent implementation case studies has shown that insurers that applied anomaly detection algorithms have been able to increase fraud detection rates by 38 percent and short fraud-related claims settlement time by a quarter [19]. This explains the role of predictive analytics in further improving security but also in optimization of the cycle time directly.

In addition to operational efficiency, predictive analytics may also change the customer experience and interaction. Customer interaction level implementation helps the insurers to predict the customer demand and provide personalized solutions. Predictive customer analytics solutions are able to predict renewal of policies, probable churn, and offer tailored health programs. As an example, predictive engagement systems, which combine behavioral and claims data, enable insurers to act proactively and give wellness incentives or individualized communication plans to retain high value customers. The implementation of these tools has an indirect effect on the efficiency of operations in that it lowers the churn rates and stabilizes the workflow demands.

Predictive analytics implementation needs an underlying technological and organizational infrastructure. Predictive deployment is built on the foundations of cloud computing platforms, data lakes, and predictive analytics applications like Python, R, TensorFlow. Nevertheless, technical infrastructure is not enough. The success of implementation also relies on organizational elements, such as data governance, employee training, and change management. It has been found out that the insurers that have a committed analytics governance staffs and cross-functional data scientific departments show an increased success in the integration of predictive analytics [20]. An organized governance system is a system of accountability, ethical control and constant correspondence between analytical results and business objectives.

The cycle time optimization process flow (Figure 2) shows the way in which the predictive analytics inter-relates with the operational processes. Ingersion and data cleaning form the starting point of the process, which is succeeded by the deployment of the predictive model that classifies or scores operational tasks. Task routing, i.e. claims approval, underwriting assessment or fraud alerting, is determined based on automated decision rules based on model outputs. Performance measures: Processing time, error rate, customer satisfaction feedback: Performance measures have continuous loops fed into retraining loops on models. This cyclic process is the functional expression of the predictive analytics integration where every process cycle of the system results in the subsequent reduction of the cycle time and the higher efficiency.

Essentially, successful implementation of predictive analytics in health insurance requires the mix of technology, processes, and people to work harmoniously. Insurers can shift their management paradigm to bring proactive optimisation, instead of reactive management, by integrating predictive systems into the working processes and setting up of feedback-based governance systems. These cycle time, accuracy and customer satisfaction improvements make predictive analytics a strategic necessity in the development of health insurance operations.

6. Challenges and Ethical Issues

Despite the substantial benefits of predictive analytics in facilitating the health insurance operations, its implementation causes numerous serious challenges and ethical concerns that should be addressed to offer sustainability, equity and appeal to people. The increased application of machine learning and artificial intelligence in the decision-making process provokes the problem of data privacy, prejudice of algorithms, openness, and compliance with regulations. Uncontrollable, these problems can disrupt the quality of operations as well as the integrity of the insurers using predictive systems.

Data privacy and security is one of the most critical problems. Health insurance predictive analytics involves a lot of access to personal and medical data of high sensitivity. This dependency on the safeguarded health data exposes insurers to the dangers of data breaches, unauthorized entry, and possible abuse. Meeting the requirements of such data protection laws as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) is thus obligatory. According to studies, however, there are no standard encryption and governance protocols in data-sharing frameworks between insurers and providers, as well as third-party vendors [21]. The distributed data processing environment of cloud-based storage and machine learning models only increase compliance further. Strong data governance, encryption, and anonymization, mechanisms have to be implemented in order to ensure the confidentiality and integrity of health information.

The second significant problem is algorithmic bias, that is, when predictive models generate systematically unfair results between various demographic groups. Predictive analytics may be biased by imbalances in historical data, the unrepresentativeness of features, or biased human inputs when training the model. As an example, prediction models used to predict risks can over or underestimate the probability of claims when the training data on a population is not representative. This may have the effect of discriminative pricing or withholding of valid claims. It is noted that research is required to constantly audit the models, identify bias tools, and train fairness-aware algorithms to address such risks [22]. Formulating clear methodologies and inclusion of fairness indicators in the assessment of models are just but some of the steps towards the creation of equity in predictive systems in health insurance.

The other problem is the issue of model interpretability and transparency. Most predictive models, especially deep learning algorithms, are so-called black boxes, which are very accurate and poorly understandable. With such a controlled industry as health insurance, the decision-makers should have the ability to explain model-based results, particularly where those decisions affect the approval of claims, pricing or eligibility in the policy. An uninterpretable situation not only leads to a decrease in compliance but also undermines the trust of stakeholders. Insurers have the new trend to adopt explainable AI (XAI) methods that enable the model outputs to become understandable to technical and non-technical audiences. Open reporting practices and model documentation increase accountability and build trust between policyholders and regulators. Lastly, the implementation must be ethical and therefore a defined governance framework that incorporates technical control and corporate ethics. The frameworks of governance must include data stewardship, model validation committees, and ethical review boards. The relevance of multi-stakeholder governance to the management of predictive model implementation is highlighted by a study by Alvarez and Morton (2023) that the predictive model deployment should be managed by multi-stakeholders to guarantee that ethical principles of beneficence, justice, and autonomy are upheld throughout the analytics lifecycle [23].

Future directions

Predictive analytics are becoming a necessity in health insurance business and therefore its future should be founded on enhanced interoperability, ethical intelligence and real time flexibility of predictive systems. One possible solution is to unite both artificial intelligence (AI) and predictive analytics to have self-educated insurance ecosystems that continuously optimise functions. The congruence of AI and predictive analytics is also allowing insurers to transcend the fixed forecasting to prescriptive and autonomous decision making systems. These systems can transform the processes of claims, underwriting boundaries and fraud controls with real time market and behavioural data [24]. This variable aspect possesses a potential of a significant reduction in the cycle times and improved accuracy without the need to be manually fixed.

The other immediate trend is that the blockchain technology is being utilized to support the integrity and transparency of the information in the predictive analytics models. Blockchain should be able to offer the safe and unalterable portion of health and insurance data among the stakeholder to enhance confidence and compliance to privacy laws. It is hypothesized that the blockchain-based predictive analytics will solve outdated challenges of fragmentation and recreation of data within the insurance systems [25]. Besides, predictive models that run on shared data and do not violate individual privacy can also be implemented through the distributed ledger technology to provide decentralized data management. Such integration is capable of introducing a more efficient, responsible, and transparent predictive insurance data infrastructure.

The role Internet of Things (IoT) and wearable devices in the enhancement of predictive datasets is also among the future research areas. The statistics of the continuous health monitoring will result in the more precise risk prediction models that will enable the insurers to provide preventive wellness programs and adhere to the dynamic pricing of premiums. In addition, data scientists, ethicists, and healthcare experts will have to work together in an interdisciplinary manner to establish and deploy responsible models. The future of predictive analytics frameworks can grow with regarding to these research priorities; producing fully automated and ethical frameworks that are capable of sustaining long term optimization of the operational processes of health insurance.

7. Conclusion

The fact is that the introduction of predictive analytics into health insurance processes is the start of the paradigm shift in the management experience of outdated and reactive goals to active and data-based optimization. The modeling predictive will also help the insurers to streamline their operation, reduce the time spent in claims and underwriting as well as improve on the risk management and fraud avoidance. The model suggested in this review is the model of integration based on the feedback that involves aligning of the data, technology and governance that may contribute to the optimization of the cycle time in the long run. However, in order to reap the benefits of forecasting analytics to the full extent, the existing obstacles of quality of the data, bias, and ethics control should be overcome. Practices Future AI, blockchain, and IoT development will enhance the agility, security, and interpretability of predictive systems. Lastly, predictive analytics is also a strategic also empowerer of a more efficient, fair, and transparent health insurance system instead of a technology innovation.

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