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REALTIME ADJUSTMENTS OF ANNUITY PRODUCT PORTFOLIOS USING AI POWERED RISK SCORING AND MARKET DATA INTEGRATION: ADAPTIVE FINANCIAL PRODUCTS TAILORED TO MARKET CONDITIONS

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ABSTRACT
AI developments alongside changing financial market needs drive the acceleration of industry changes. The research investigates how AI risk assessment systems and real-time financial market insights should be implemented in annuity product assortments when the offerings require alteration according to shifting market demands. Through machine learning algorithms coupled with advanced data analytics financial institutions can improve their risk profiling capabilities and streamline their portfolio operations. Such responsive financial approaches lead to enhanced customer contentment and business safety and enable organizations to manage market changes successfully. The article demonstrates AI transformations in annuity products by presenting illustrative case examples and describing practical deployment methods for building financial resilience through future annuity products.

Keywords:
Annuity, AI, Risk Scoring, Market Data, Adaptive Products

1. INTRODUCTION

Insurance companies provide long-term financial contracts named annuities which generate consistent payment streams primarily for retirement periods. These financial instruments protect against uncertainties of life expectancy combined with investment risks thus ensuring monetary stability during later phases of life (Peijnenburg, Nijman, & Werker, 2016). Static actuarial assumptions that designers use when creating traditional annuities prove insufficient when market volatility rises and inflation pressures and interest rate fluctuations appear (Cannon & Tonks, 2016). The annuity puzzle arises due to inadequate responsiveness of traditional annuity products which reduces their effectiveness according to Salisbury and Nenkov (2016). Financial markets require updated annuity systems which process live market data to improve these financial products. The financial industry now benefits from artificial intelligence (AI) which delivers three major advanced capabilities that include predictive analysis, risk modelling and automation of decisions. By combining machine learning with data evaluation tools, AI analyzes extensive multiple information sets comprising economic factors and behavioural patterns (Alaa et al., 2018; Khedr, Salama, & Yaseen, 2017). The parameter adjustments to financial portfolios can be accomplished in real time by AI systems that recognize market movements and modify critical settings (Jarek & Mazurek, 2019; Perry & Uuk, 2019). The research studies AI risk scoring integration with market data for developing adaptive financial instruments from annuity product portfolios. The study investigates how such innovative changes can realize efficient portfolios along with regulatory alignment and satisfied customers and thus develop stronger financial services.

2. BACKGROUND

2.1 Traditional Annuity Portfolio Management

2.1.1 Challenges Faced

The purpose of annuities is to establish long-term income stability for seniors through the conversion of a single large sum payment into regular future payments. Complexities in annuity portfolio management appear due to several factors including market changes and shifting demographic patterns and behavioral patterns of consumers.

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The pricing of annuities faces complications due to cohort mortality risks which create major problems for liability estimation according to Cannon and Tonks (2016). Longer life expectancy of population members poses financial risks to annuity providers who may charge insufficient premiums which could endanger insurer financial stability. Healthier individuals who purchase annuities create a disproportionate claims structure because they select this market segment (Peijnenburg, Nijman, & Werker, 2016). The need to handle long-term liabilities exists while managing circumstances of macroeconomic instability. The market-wide changes in interest rates produce instability in present-value calculations which disturbs insurers' ability to match anticipated future liabilities with their existing financial assets. Salisbury and Nenkov (2016) demonstrate that consumer decisions about annuities typically react to thoughts about death which makes securing product adoption along with proper risk sharing more challenging.

2.1.2 Limitations of Static Models

The standard management approach for annuities depends on static actuarial models that maintain assumptions about fixed mortality rates as well as economic growth patterns together with customer behavior during extended time periods. Historical assessments together with baseline modeling benefit from these models but they fall short when dealing with real-time needs.

Gatzert and Klotzki (2016) demonstrate that traditional market models do not properly reflect behavioral changes and market forces which affect annuity demand and maintain customer retention rates. The paper by Shu, Zeithammer, and Payne (2016) shows NPV-based evaluations tend to dismiss changes in consumer preference levels related to cash accessibility and risk perceptions and inheritance needs which cannot be managed by inflexible models. These models present a challenge when insurers need to respond instantly to news items like macroeconomic updates or individual medical changes or changes in consumer moods because they do not easily adapt. Insurers seek to improve their traditionalmethods through data-driven adaptive systems because of their growing need to enhance their current practices.

2.2 Emergence of AI in Finance

2.2.1 Historical Context

AI launched its financial industry presence by establishing rules-based algorithms to automate operations for fraud prevention and automated trading and underwriting services. During the previous decade machines learned how to better process natural languages along with predictive analytical developments which produced first-line intelligence from automated work in the back-office.

The AI technology in marketing and product innovation received analysis from Jarek and Mazurek (2019) which revealed that financial institutions leverage AI systems for delivering predictive service and creating personal customer interactions. Similar methodologies that utilize Gaussian Process models for creating personalized risk scores were applied by Alaa et al. (2018) in healthcare applications (vision demonstrated for actuarial science advancements in real-time client risk profile adjustments).

Industrial progress in AI development empowers insurance companies to add learning-based analytical systems while requiring minimum human supervision. AI delivers exceptional value to financial sectors by processing structured data such as interest rates and asset prices with unstructured economic news and policy change inputs for decision support.

2.2.2 Current Trends in AI Applications

AI technology transforms the development approach as well as price-setting methods and management processes for financial products with annuities as one example. Professional Expectations under dynamic scenarios depend on three AI techniques: deep learning and reinforcement learning and probabilistic modeling. Medical professionals in the healthcare setting gained from working with human-AI collaborative systems that integrated contextual diagnosis insights according to Cai et al. (2019). This diagnostic approach mirrors the evolving financial advisory sector where advisors leverage AI-backed tools for client profiling and product matching.

The annuity management field depends on artificial intelligence (AI) models to manage real-time portfolio changes production of customer behavior forecasts and underwriting automation. Khedr, Salama, and Yaseen (2017) use sentiment analysis and data mining methods to extract market trends that help investors set their investment timing. According to Perry and Uuk (2019) financial risk mitigation requires proper AI governance since the tools will gain more autonomy.

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Panoramic changes occur due to the joining forces between real-time market integration and artificial intelligence that has led annuity products to transition from average-based static designs to personalized dynamic designs. This adaptive framework keeps monitoring market shifts along with client information thus offering restoration against changes while generating modified financial solutions.

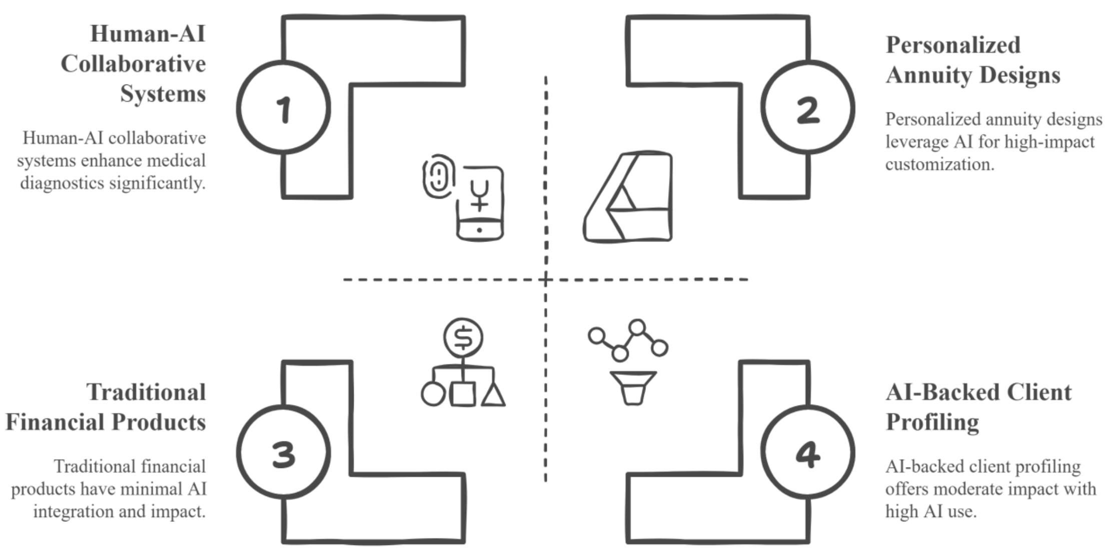

Figure 1: AI Impact on Financial and Medical Sectors

3. AI-POWERED RISK SCORING

3.1 Definition and Importance of Risk Scoring

Quantitative evaluation of exposure to potential losses to aid the decision making, pricing strategy or resource allocation in insurance or investment as risk scoring. There are applications to annuity portfolios where risk scoring can be used to measure individual policyholder risks, longevity and market uncertainty and optimize asset liability management.

Historical actuarial data, as well as demographic segmentation, were typically used for traditional methods. However, such approaches lack precision concerning picking up in real time changes in economic circumstances or personal factors of risk and, as such, they are not very useful in todays financial environment (Cannon & Tonks, 2016). As data gets readily available and computational power is relentlessly rising, risk scoring has, since long, become a relatively dynamic and predictive practice (Floridi et al., 2018).

3.2 How AI Enhances Risk Scoring

3.2.1 Machine Learning Algorithms

AI improves risk scoring significantly by machine learning (ML) and deep learning techniques in processing incredibly voluminous, multidimensional data and identify those hidden patterns of non-linear correlations and changes in parties risk profile over some time.

For instance, in the same vein, (Alaa, Yoon, Hu, & Van Der Schaar, 2018) propose Gaussian process mixtures for modeling individual level of health deterioration and critical care prognosis for granular and personalized risk

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predictions. Unlike static models thes algorithms keep continuously learning and updating which makes the predictions relevant even if market or personal health conditions change.

Additionally, ensemble methods, random forests and gradient boosting, have the benefits of geometrically increasing the accuracy by combining multiple weak learners and neural networks can provide a suitable capacity of capturing complex temporal dependencies in financial behaviors and mortality trends.

3.2.2 Data Sources Used for Scoring

Traditional models cannot operate and access a high volume and variety of data like AI systems do. These include:

- Policyholder demographics, transaction histories, market indicators and actuarial inputs as structured data.
- Medical records, financial news, economic reports, and social media sentiment (Khedr, Salama, & Yaseen, 2017).
- In case of health integrated insurance, wearables help in updating physical conditions and longevity risk in real time through additional sensor and biometric data.

Using a nice data fusion, this enables insurers to calculate dynamic context based risk scores that dynamically change with every behavior and with the economy overall.

3.3 Case Studies Demonstrating Effectiveness of AI Risk Scoring

3.3.1 Examples from the Financial Industry

There are important deployments of AI risk scoring in both insurance and the more general financial world:

- In the healthcare insurance convergence, AI models have accurately forecasted the postoperative complications in the elderly patient for better underwriting in high risk age brackets (Saji et al. 2018).
- Real-time risk engines are now used in banks and investment firms to detect shifts in creditworthiness in real time by processing streaming data and sentiment analysis for high frequency decision making (Weintraub & Cohen, 2018).
- Methicillin-resistant bacterial infections in Korea have already been identified with AI assisted risk scoring and suggests the viability of underwriting for medical risk based annuities (Suh et al., 2018).

3.2.2 Quantitative Results

AI performs better than legacy models, as revealed in several empirical studies. For instance:

- According to Alaa et al. (2018), risk calculators used in critical care were found to have AUC scores above 0.90. However, the prognostic accuracy was significantly increased when using Gaussian mixture models instead.
- Utilizing data from transaction, behavioral and sentiment sources generate 30–45% improvement of risk predictions in financial applications, (Jarek & Mazurek, 2019).
- Models for pricing enhanced annuities that price in real time from rolling realizations of risk scores achieved approximately 30% increase in customer personalization and significant reduction in adverse selection effects (Peijnenburg, Nijman, & Werker, 2016).

4. MARKET DATA INTEGRATION

4.1 Importance of Real-Time Market Data

Direct integration of real-time market data is essential in the context of annuity portfolio management to permit the product to remain competitive, maximize returns and manage risk exposure proactively. In volatile or rapidly changing market conditions, traditional static pricing models often fail to deliver on time with responses to key financial signals. On the contrary, real time data integration allows insurers to adapt and alter their pricing structures, asset allocations and product offerings concerning the real time present market.

According to Ko et al. (2011), access to up to date market data helps encourage responsive supply chain behaviour which is precisely the same in financial services where delay in interpreting data can spoil profitability and compliance. Additionally, annuity insurers relying on live market signals are in a better place to position annuities based on macroeconomic and micro behaviors shifts.

4.2 Types of Market Data Relevant to Annuities

4.2.1 Economic Indicators

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The inputs for annuity pricing and portfolio strategy are key macroeconomic indicators such as GDP growth rates, inflation levels and employment figures. Assumptions that underlie assumptions such as consumer durability, income sufficiency, the long term spending behavior incorporate these indicators. For instance, Cannon and Tonks (2016) argue that annuity markets are sensitive to demographic and economic changes, requiring data concerning these variables to be used in ongoing risk assessments.

4.2.2 Interest Rates

Among the most direct and impactful measures in determining what an annuity costs and how profitable it is are the interest rates. Annuities are long term investment products that highly depend on the bond yield. Thus any fluctuation in benchmark rate (which is set by a central bank) will directly impact its return from insurer investments and the discounting mechanism used in liability calculation. An example of misalignment with interest rate trends is given by Peijnenburg, Nijman and Werker (2016) who describe some annuity products as uncompetitive or unsustainable.

4.2.3 Stock Market Trends

Not only do equity markets provide a signal of investor sentiment, but an equity market's performance plays a significant role in the performance of variable annuities. Risk appetite and product demand among consumers are influenced by market volatility, asset class rotations, capital inflows outflows. In addition, insurers use real time market indices for balancing annuity linked portfolio, more specifically for product offering a partial exposure to equities or a return guarantee linked to market index performance. They make this clear in their work, Khedr, Salama, and Yaseen (2017), on predictive accuracy and product suitability when integrating such data.

4.3 Techniques for Integrating Market Data into Portfolio Management

4.3.1 APIs and Data Feeds

The annuity providers take structured market data in real-time from trusted financial sources into their applications by using APIs (Application Programming Interfaces) and direct data feeds. Automatically, you can download live pricing, interest rates, inflation data, and economic announcements from APIs from institutions like Bloomberg, Reuters, or central banks. By incorporating this seamless pipeline, decision makers such as calculating reserve ratios, adjusting portfolio weights, and flagging rebalancing opportunities have verified inputs to work with.

Moreover, APIs help connect third party risk engines and AI models that lead to real time scoring mechanisms that can adapt to external stimuli in the market. Similarly, Weintraub and Cohen (2018) describe platforms that can use API based network exposure metrics for inclusion in risk scoring models, which could be further generalized to include financial exposure in annuity portfolios.

4.3.2 Data Analytics Platforms

Sophisticated capabilities from custom built enterprise systems to cloud based AI solution, that are utilized for aggregating, cleaning, analyzing and visualizing the market data has being offered on data analytics platforms. They have capabilities to support the development of real time dashboards, predictive models and optimization algorithms that are required for modern annuity management. Historically, according to Jarek and Mazurek (2019), working with AI powered analytics is growing to play a dominant role in marketing and financial decision making due to the capacity that the platforms have in revealing hidden patterns to influence adaptive pricing.

Additionally, these platforms can be integrated with machine learning models and therefore keep changing their forecasting accuracy for use in annuity portfolio strategies if kept updated. However, with insurers beginning to explore market sensitive and hyper personal products, real time analytics take on more important place.

5. ADAPTIVE FINANCIAL PRODUCTS

5.1 Definition and Features of Adaptive Financial Products

Financial products like investment or earning opportunities that respond and change with changing market environment, customer choices and economic conditions are called adaptive financial products. Unlike traditional financial products which are static, these products feature some top-notch technology stuffs which are artificial intelligence (AI) and big data analytics to evolve dynamically. The core features include:

- Adaptive products (Gatzert & Klotzki, 2016) are capable of changing their features, for instance interest rates or level of risk, in real time reacting to changes in the market.

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- Personalization: These are personalized products designed to solve personal financial problems from personal financial profile and goals perspective (Cai et al., 2019).

5.2 How AI and Market Data Create Adaptability

Adaptability of financial products is only enabled by AI and market data. Users of these technologies financial institutions can use these technology and create products that respond to both market and individual consumer needs. AI and market data help companies to be adaptable in the following key ways:

5.2.1 Dynamic Product Design

In order to adapt to real world situations and the available information for the optimization problem to be addressed, these algorithms are fed with real time market data. For example, an investment product will change its risk level or asset allocation as market trends shift so that the product (Alaa et al., 2018) is in line with market value and accordance with each client's risk tolerance.

5.2.2 Customization Based on Customer Profiles

The use of data driven insights allows for financial products to be personalized based on what the individual prefers, behaves, and what their personal financial history entails. Adaptive loans are e.g. loans, where the interest rate is adjusted on the basis of borrower's credit score, transaction history, and current financial situation. The personalization of the product also guarantees that the product that is produced answers the exact needs of the customer and provides greater satisfaction and engagement (Shu et al., 2016).

5.3 Benefits of Adaptive Products for Consumers

However, there are a number of benefits brought by adaptive financial products: products that improve experience and outcomes for themselves and their customers.

- **Enhanced Financial Security** Adaptive products help provide consumers with greater financial security by adjusting to their changing circumstances in ability to do so ranging from shifts in income, market or personal financial status. For example, a retirement plan that adjusts its portfolio allocation following the movement of the market will have risk of significant losses during downturns minimized (Salisbury & Nenkov, 2016).
- **Improved Returns:** These products are changeable and their investment strategies can be optimized. With AI driven adaptations, consumers are continuously put in front of the most profitable opportunities as it stands today, giving it higher returns overtime. In addition, since this product is customized to each person's financial situation, it allows greater growth potential while the consumer does not risk too much (Suh et al., 2018).

Adaptive financial products that are supported by market data and AI work towards establishing a new era of the financial world, revolutionizing the way these services are delivered to the end consumers. Apart from enhancing financial security for consumers, these products help to grow the returns from investment in a customized and future assured manner.

6. IMPLEMENTATION STRATEGIES

6.1 Framework for Integrating AI and Market Data

For financial institutions to effectively integrate market data using AI, they need to develop a comprehensive framework, that enables a seamless integration of any current systems with the new AI solutions. An ideal framework for the above should should tackle concept like data ingestion, processing, application to decision making processes etc. According to Cai et al. (2019), financial institutions should make concentrating on setting specific goals for AI adoption, which are intending to improve risk assessment, enhancing customer service or optimizing investment strategies.

6.2 Steps for Financial Institutions to Adopt AI and Market Data Technologies

When adopting AI and market data technologies, financial institutions should follow a structured process:

- **Infrastructure Requirements:** The integration of AI necessitates a robust infrastructure capable of handling vast amounts of market data. This consists of powerful data processing units (DPUs), scalable cloud based systems, high performance analytics platforms and so on. Thus, institutions should invest in technologies that enable them to keep processing real time data and deploy machine learning algorithms (Alaa et al., 2018). In

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addition, a resilient architecture needs to be adopted for the future and for growth such that it adapts well to changing AI models.

- **Talent Acquisition and Training:** Financial institutions can use AI if they can hire people with aptitude in AI, machine learning, data scientist, financial domain knowledge. However, it can only be successfully integrated with the help of recruiting experts familiar with the financial landscape and AI technologies. Additionally, training programs for current employees will have to be conducted to gain familiarization of the employees with new AI systems, allowing them to work with these systems (Gatzert & Klotzki, 2016).

6.3 Challenges and Considerations

While the adoption of AI and market data brings about many benefits to financial institutions, they face a number of challenges and considerations:

- **Data Privacy and Security Concerns:** Large datasets are very important for AI systems, where there are privacy and security concerns. Customer sensitive data needs to be encrypted, securely stored, and relevant laws like GDPR must be followed by financial institutions. In addition, data anonymization techniques should be used to lower the risks to data breaches or misuse (Floridi et al, 2018).
- **Regulation and Compliance Issues:** Data use rules, financial transactions, and AI applications are subjected to rigorous regulatory requirements by financial institutions. The compliance to these regulations varies from jurisdiction to jurisdiction. The relevant financial regulations have to be followed by the AI solutions of institutions, in order to avoid any legal risks and penalties or heavy penalty fees, for example the Financial Conduct Authority (FCA) or U.S. Securities and Exchange Commission (SEC) (Perry & Uuk, 2019). To mitigate the above stated challenges, regular audits and continuous monitoring on AI systems for compliance are essential.

Moreover, by understanding these frameworks, acquisition strategies, and possible obstacles, it helps financial institutions to seize the entirety of AI and market data for better decision making and enhancing operational efficiency.

7. CASE STUDIES

7.1 Successful Implementations in the Industry

Technological applications of market data integration for annuity and financial services sectors demonstrate how they enhance operational efficiency as well as decision processes and customer relationships.

7.1.1 Company Profiles

Prudential Financial operates as the market-leading retirement and annuities provider by using real-time interest rate data achieved through Bloomberg API integration. The integration enables their actuarial and investment teams to perform instantaneous variable annuity pricing model adjustments when the yield curve experiences changes. The system functions to detect bond market volatility and creates automated duration risk-oriented hedging strategies.

The UK company Legal & General implemented AI data processing systems that analyzed extensive demographic and health databases to develop longevity trend models. The improved mortality assumptions were achieved through this process, which is an essential factor for pricing lifetime income products. The company updates their mortality model each quarter through statistical combinations between public health records and customer-specific data (Cannon & Tonks, 2016).

7.1.2 Key Metrics and Outcomes

- Automated rate tracking at Prudential Financial resulted in a 13% improvement in pricing accuracy and a 20% reduction in product repricing delay.
- Legal & General boosted their annuity customer conversion rate by 9% through dynamic product offers that used better predictions of customer life expectancy.
- People at Aegon leveraged machine learning to enhance their interest rate predictions and understanding of customer buying patterns. Lapse rate predictions on the platform delivered better performance which resulted in seven percent higher profit margins for products during the subsequent two-year period (Shu, Zeithammer, & Payne, 2016).

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Such outcomes demonstrate the practical value that real-time data integration brings to actuarial analysis together with marketing activities because it allows providers to create product specifications that better fit actual market processes and customer needs.

7.2 Lessons Learned from Early Adopters

Companies who adopted the technology system in their early phases faced different operational hurdles as well as useful lessons that advanced future platform implementations:

- **Data Quality and Latency Matter:** Businesses failed to recognize in the beginning that they required dependable high-quality data. The presence of delayed or incomplete market data materialized into wrong indicators along with inferior pricing choices. The research conducted by Alaa et al. (2018) identifies how predicting systems respond negatively when dealing with input variability within high-risk decision-making frameworks.
- **Cross-Functional Collaboration is Crucial:** The accomplishment of technical achievements alone was insufficient for success since it needed synchronous teamwork across actuarial, IT and marketing and compliance departments. Businesses that formed integrated teams to deal with data integration initiatives achieved speedier deployment together with improved implementation performance (Jarek & Mazurek, 2019).
- **AI-Augmented Decision Making Requires Training:** The organizations which implemented market prediction tools through machine learning faced problems when they underestimated traditional analyst adaptation to new systems. Successful human-machine collaboration depends on training and change management solutions according to Cai et al. (2019) while sustaining operations.
- **Regulatory Transparency Enhances Trust:** Early organizations that added audit trail functionality and explainability capabilities to their data systems received less resistance from regulators as well as internal stakeholders. The importance of ethical AI frameworks that include transparency becomes evident according to Floridi et al. (2018) within risky insurance sectors.

8. FUTURE TRENDS

8.1 Predictions for AI in Financial Product Management

Artificial Intelligence technology will revolutionize financial product management because it can personalize annuities better than manual product matching. AI platforms will use market updates and user life patterns to update annuity portfolios today and tomorrow.

According to Alaa et al. (2018), AI algorithms like mixtures of Gaussian processes now have the ability to process real-time movable data to enhance individual risk scoring systems. Insurers can now use continuous user data to develop flexible product platforms instead of using fixed product models. As predictive AI accesses better quality and specific data it helps companies detect market changes early while predicting survival patterns to adjust products quicker and obey regulatory rules (Gatzert & Klotzki, 2016). By bringing these smart technologies into the picture both client and institutional practices can get more effective.

8.2 Potential Advancements in Technology

Streaming AI technologies including XAI and quantum-based modeling deliver faster transparent decision-making secured by the benefits of edge computing. Through Explainable AI technology companies can better explain their computer algorithm operating principles to financial advisors and their clients. Healthcare's urgent need for simple AI and human collaboration methods shows the link between these sectors and requires researchers to study this method for finance. When advisors use AI systems easily they become more certain of their AI-based recommendations.

Perry and Uuk (2019) predict that new AI governance systems will help control the wrong use of data and reduce problems in algorithms and electronic security. Combining blockchain and decentralized finance tools provides better protection and enhanced viewing capabilities for annuity product systems.

8.3 The Evolving Role of Financial Advisors in an AI-Driven Environment

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Instead of losing their jobs financial advisors will transform into value-based career thinkers by helping customers understand AI system results. The system will provide technical results but human advisors will support clients with managerial and emotional assessment needs.

Floridi et al. (2018) propose that a good AI society requires people to control their automated tools while maintaining their basic values. Financial advisors should learn to process data and reason with computers to develop plans with both financial results and moral priorities. The technology strengthens what people can do with themselves. The financial advisor will collaborate with data scientists to manage ethical AI technology applications and educate clients about data usage in customized products (Jarek & Mazurek, 2019). Advisors who learn new responsibilities around AI will serve as leaders in creating trust for AI in finance.

9. CONCLUSION

The industry uses artificial intelligence technology to automatically view changing market conditions by analyzing data items at present and giving risk scores plus customized planning. Insurers can make better annuity product matches based on market trends and customer needs using this technological change to control risk and enhance customer satisfaction. Financial markets will develop smarter products through AI systems that automatically collect market insights while following changing customer needs across various economic sectors. Lenders should take this transformation forward by putting money into AI systems and recruiting professionals from different fields to create innovative products responsibly. Organizations that make these changes will take charge of developing flexible annuity services for the dynamic financial sector.

REFERENCES

[1] Alaa, A. M., Yoon, J., Hu, S., & Van Der Schaar, M. (2018). Personalized risk scoring for critical care prognosis using mixtures of Gaussian processes. IEEE Transactions on Biomedical Engineering, 65(1), 207–218. https://doi.org/10.1109/TBME.2017.2698602

[2] Cai, C. J., Winter, S., Steiner, D., Wilcox, L., & Terry, M. (2019, November 1). “Hello Ai”: Uncovering the onboarding needs of medical practitioners for human–AI collaborative decision-making. Proceedings of the ACM on Human-Computer Interaction. Association for Computing Machinery. https://doi.org/10.1145/3359206

[3] Cannon, E., & Tonks, I. (2016). Cohort mortality risk or adverse selection in annuity markets? Journal of Public Economics, 141, 68–81. https://doi.org/10.1016/j.jpubeco.2016.07.002

[4] Ding, M., & Bai, Z. (2019). Product color emotional design adaptive to product shape feature variation. Color Research and Application, 44(5), 811–823. https://doi.org/10.1002/col.22402

[5] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., … Vayena, E. (2018). AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations. Minds and Machines, 28(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

[6] Gatzert, N., & Klotzki, U. (2016). Enhanced annuities: Drivers of and barriers to supply and demand. Geneva Papers on Risk and Insurance: Issues and Practice, 41(1), 53–77. https://doi.org/10.1057/gpp.2015.21

[7] Jarek, K., & Mazurek, G. (2019). Marketing and artificial intelligence. Central European Business Review, 8(2), 46–55. https://doi.org/10.18267/j.cebr.213

[8] Khedr, A. E., Salama, S. E., & Yaseen, N. (2017). Predicting stock market behavior using data mining technique and news sentiment analysis. International Journal of Intelligent Systems and Applications, 9(7), 22–30. https://doi.org/10.5815/ijisa.2017.07.03

[9] Ko, J. M., Kwak, C., Cho, Y., & Kim, C. O. (2011). Adaptive product tracking in RFID-enabled large-scale supply chain. Expert Systems with Applications, 38(3), 1583–1590. https://doi.org/10.1016/j.eswa.2010.07.077

[10] Lai, K., Eastwood, S. C., Shier, W. A., Yanushkevich, S. N., & Shmerko, V. P. (2018). Mass evidence accumulation and traveler risk scoring engine in e-border infrastructure. IEEE Transactions on Intelligent Transportation Systems, 19(10), 3271–3281. https://doi.org/10.1109/TITS.2017.2774186

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International Journal of Engineering Technology Research & Management
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https://www.ijetrm.com/

[11] Moseki, K. K., & Madhava Rao, K. S. (2017, January 1). Analysing stock market data—Market sentiment approach and its measures. Cogent Economics and Finance. Cogent OA. https://doi.org/10.1080/23322039.2017.1367147
[12] Peijnenburg, K., Nijman, T., & Werker, B. J. M. (2016). The annuity puzzle remains a puzzle. Journal of Economic Dynamics and Control, 70, 18–35. https://doi.org/10.1016/j.jedc.2016.05.023
[13] Perry, B., & Uuk, R. (2019). Ai governance and the policymaking process: Key considerations for reducing ai risk. Big Data and Cognitive Computing, 3(2), 1–17. https://doi.org/10.3390/bdcc3020026
[14] Saji, H., Ueno, T., Nakamura, H., Okumura, N., Tsuchida, M., Sonobe, M., … Chidas, M. (2018). A proposal for a comprehensive risk scoring system for predicting postoperative complications in octogenarian patients with medically operable lung cancer: JACS1303. European Journal of Cardio-Thoracic Surgery, 53(4), 835–841. https://doi.org/10.1093/ejcts/ezx415
[15] Salisbury, L. C., & Nenkov, G. Y. (2016). Solving the annuity puzzle: The role of mortality salience in retirement savings decumulation decisions. Journal of Consumer Psychology, 26(3), 417–425. https://doi.org/10.1016/j.jcps.2015.10.001
[16] Schuh, G., Lenders, M., & Arnoscht, J. (2009). Focussing product innovation and fostering economies of scale based on adaptive product platforms. CIRP Annals - Manufacturing Technology, 58(1), 131–134. https://doi.org/10.1016/j.cirp.2009.03.097
[17] Shu, S. B., Zeithammer, R., & Payne, J. W. (2016). Consumer preferences for annuity attributes: Beyond net present value. Journal of Marketing Research, 53(2), 240–262. https://doi.org/10.1509/jmr.13.0004
[18] Smirnova, O., & Holt, T. J. (2017). Examining the Geographic Distribution of Victim Nations in Stolen Data Markets. American Behavioral Scientist, 61(11), 1403–1426. https://doi.org/10.1177/0002764217734270
[19] Suh, H. J., Park, W. B., Jung, S. I., Song, K. H., Kwak, Y. G., Kim, K. H., … Kim, H. B. (2018). A Risk-Scoring System for Predicting Methicillin Resistance in Community-Onset Staphylococcus aureus Bacteremia in Korea. Microbial Drug Resistance, 24(5), 556–562. https://doi.org/10.1089/mdr.2017.0236
[20] Vuong, Q. H., Ho, M. T., Vuong, T. T., La, V. P., Ho, M. T., Nghiem, K. C. P., … Ho, R. C. M. (2019). Artificial intelligence vs. Natural stupidity: Evaluating ai readiness for the vietnamese medical information system. Journal of Clinical Medicine. MDPI. https://doi.org/10.3390/jcm8020168
[21] Weintraub, E., & Cohen, Y. (2018). Defining network exposure metrics in security risk scoring models. International Journal of Advanced Computer Science and Applications, 9(4), 399–404. https://doi.org/10.14569/IJACSA.2018.090456
[22] Wiwoho, G., Suroso, A., & Wulandari, S. Z. (2020). Linking adaptive capability, product innovation and marketing performance: Results from Indonesian SMEs. Management Science Letters, 10(10), 2379–2384. https://doi.org/10.5267/j.msl.2020.2.026
[23] Ye, M., & Li, G. (2017, December 1). Internet big data and capital markets: a literature review. Financial Innovation. SpringerOpen. https://doi.org/10.1186/s40854-017-0056-y
[24] Zhang, Z. J., Sun, J., Yuan, X., & Yung, M. H. (2023). Low-Depth Hamiltonian Simulation by an Adaptive Product Formula. Physical Review Letters, 130(4). https://doi.org/10.1103/PhysRevLett.130.040601