Individual Essay: Artificial Intelligence and its Applications: Final Submission

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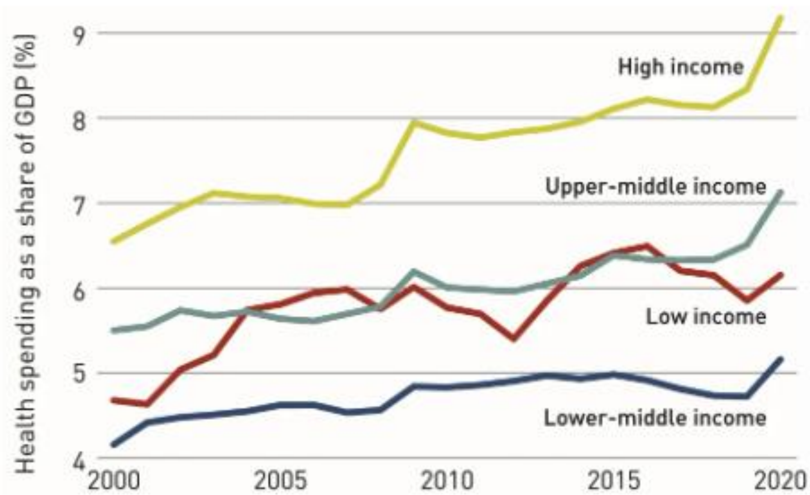
Report Title

Enhancing Competitive Advantages through Artificial Intelligence (AI) Integration in your Healthcare Finance Company: All Health Finance Ltd.

Introduction to Company Details and Industry Focus

All Health Finance Ltd (AHF) is a start-up finance company on a mission to bring affordable healthcare to everyone, everywhere. The company's vision is a world where everyone can access high quality healthcare at an affordable price. AHF delivers a range of services, including healthcare insurance for patients and healthcare investment advice for investors.

Providing financial solutions for the healthcare industry is a competitive landscape. The global healthcare finance solutions market size was valued at USD 111.0 billion in 2021 and is anticipated to grow at a compound annual growth rate (CAGR) of 7.7% (Grand View Research, 2023). Within this growing market, there are several areas where businesses can deploy AI technologies to gain competitive advantages. The business opportunity is significant, with growing elderly and comorbid populations across the globe, the cost of delivering healthcare is increasing (Statistica, 2023; WHO, 2023).



Global Health Spending (WHO, 2023)

New companies such as AHF can disrupt the market by providing alternative solutions, powered by the latest technology and the growing role of data and AI.

Three key areas for AI Integration

Integrating AI into the following key areas will improve AHF's operations and increase returns.

1. *Personalised Healthcare Insurance*

Predictive Analytics for Customised Plans: AI can be utilised to analyse patient medical history, lifestyle data, sociodemographic and genetic information to offer tailored insurance plans that provide the best value for specific customers based on their needs and risk. Providing more accurate and value-based insurance plans will increase returns because the risk is managed more effectively, and the customers have greater confidence in the quotes. They may even save money if they modify factors such as lifestyle and behaviours, thereby rewarding healthy activity and attracting more customers.

2. *Data-Driven Investment Strategies in Healthcare*

AI-Informed Healthcare Investment Portfolios: AI can analyse global healthcare trends, research and development data, medical device, biotech and pharmaceutical market data to empower investors to make more confident and informed decisions. Providing more accurate investment strategies will increase returns because investors will choose your solutions over competitors to maximise their chance of return and invest more securely.

3. *Operational Efficiency*

Healthcare-Grade AI Customer Assistants: These products should be able to understand complex medical terms and guide customers to making the best insurance and investment decisions. This will aid operations and increase returns by reducing your costs on human customer service providers, and customers may prefer your company because it is quick and easy to access high quality, personalised advice.

Potential Problems with AI Integration

There are several challenges with integrating AI into AHF that must be considered and addressed.

Data Protection and Regulatory Compliance

Maintaining data-intensive systems requires companies to ensure the highest standards of data-protection, and this is even more emphasised in the health and finance industry (Murdoch, 2021). Health data is among some of the most sensitive and personal data in the world and is therefore regulated heavily. Data usage principles are provided in various regulatory frameworks including HIPAA (The Health Insurance Portability and Accountability Act) in the Unites States and GDPR (General Data Protection Regulation) in Europe (other countries have their own regulations that impact data use). These principles include confidentiality, consent and authorisation, data minimisation and purpose limitation, data security and access controls, data retention and deletion, and data audit and reviews (Forcier et al. 2019).

Errors and Bias

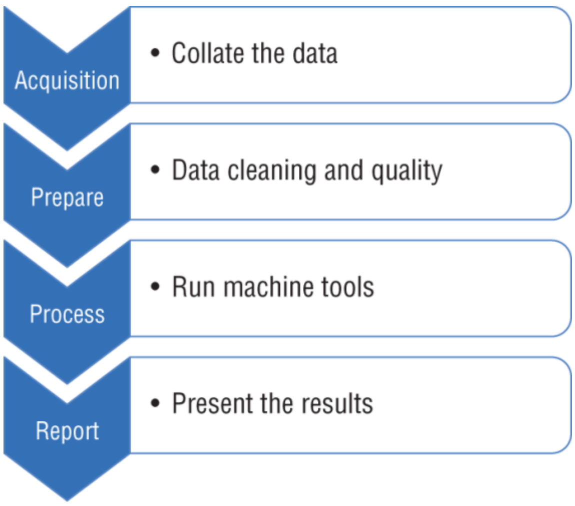
The tolerance for errors in the analysis of health and finance data is rightfully low. Accuracy and safety are among the most valued factors of output from healthcare and finance AI applications. AI models that have a high level of interpretability (technical inner workings of the models can be understood) and explainability (being able to explain decisions made to users) are often favoured to mitigate the risk of errors and biases (Amman et al, 2020; Lee et al, 2021). Inherent biases in the training datasets used by many AI applications result in underrepresented populations suffering from inequitable access and systematic errors (Celi et al, 2022). Being able to measure and mitigate bias in AI models is a critical for applications in health and finance.

Complexity of Healthcare Finance Data

Healthcare data used by AHF financial services is complex, including a range of diverse data types (e.g., imaging, genomic, clinical) and this can pose integration challenges. Different data types require different models to handle them and produce useful output. For example, deep neural networks are often required for predictions from imaging data, whereas random forest algorithms are used to traditional electronic health record data (Ngiam et al, 2019). Clinical databases often lack interoperability, and this also contributes to the complexity in this industry (e.g., isolated databases, incompatible systems) (Lehne et al, 2019).

Data Requirements & AI Deployment

General principles in the planning of AI deployments include data acquisition, database storage and data cleaning. These steps should be considered fully before any analysis starts. This is particularly important when integrating and standardising different data types and sources.



The Machine Learning Cycle (Bell, 2020).

The tables below focus on specific analysis approaches for the three key areas for AI integration presented previously.

Personalised Healthcare Insurance - Predictive Analytics for Customised Plans

Data Needed	**Approaches**	**Strengths, Weaknesses and Examples**
Electronic Patient Records (EPR) – comprehensive health data for each patient, sourced by partnering with healthcare providers. Lifestyle data – information about health behaviours and habits, sourced from customer surveys or wearable health devices. Healthcare provision costs – the cost of providing healthcare to address health needs, sourced from supplier partners.	The core function here is to be able to predict health outcomes and related costs accurately based on patient-specific data. Decision tree models are supervised learning approaches that can handle numerical and categorical information that is commonly found in these data sources. Several algorithms have been developed for decision tree analysis including ID3, C4.5, CHAID, and MARS (Bell, 2020). C4.5 algorithms may be advantageous in this case because they can handle continuous qualities in data, and they handle over-fitting be enabling pruning after creation (Bell, 2020).	Decision trees are easy to read and report through white-box testing, and therefore have increased interpretability and explainability that may be valuable to customers and regulators (Bell, 2020). The main limitations of this approach include concerns with over-fitting data, and this is why data-pruning is so important (Bell, 2020) In healthcare finance, decision tree models can predict diagnoses and progress of a disease, and combined with cost data, this can be used to set customised prices for customers (Nithya and Ilango 2017).

Data-Driven Investment Strategies in Healthcare - AI-Informed Healthcare Investment Portfolios

Data Needed	**Approaches**	**Strengths, Weaknesses and Examples**
Global healthcare trends – sourced from national health statistics databases and partners**.** Patent and R&D data – sourced from national patent repositories and R&D expenditure reports.	The core function here is to segment investment opportunities and identify emerging trends or patterns using clustering. Clustering models are unsupervised learning approaches that allows you to find structure within data.	Clustering models are useful because they can handle unlabelled data (Bell, 2020). Data labelling can be extremely time consuming and costly. The main limitations of clustering models include sensitivity to initial

	A common clustering algorithm is k-means, and others include hierarchy clustering and clustering based on density and distribution (Xu and Tian, 2015).	parameters such as number of clusters, and experimentation to optimise the initialisation process can reduce error (Frånti and Sieranoja, 2019). In finance and investing, clustering models have been shown to improve decision efficiency in investment portfolio diversification (Palupi et al, 2019).

Operational Efficiency - Healthcare-Grade AI Customer Assistants

Data Needed	**Approaches**	**Strengths, Weaknesses and Examples**
User data – the AI assistant needs to have access to the full user database so it can provide personalised responses. Medical knowledge database – comprehensive and up to data database of medical information. Feedback data – user feedback on the performance of the AI assistant.	The core function here is to provide customers with a human-like interaction that can augment many customer service tasks. One initial approach to begin to develop this tool is the Word2Vec algorithm, a type of natural language processing algorithm, (Bell, 2020; Mikolov et al, 2013). This is an embedding model where a word's meaning can be inferred by the words that appear closer to it in vector space. Creating a health finance-specific model would provide a key competitive advantage.	Word2Vec is particularly strong at identifying semantic relationships which could be useful to link conditions and medications with related healthcare costs and outcomes. Weaknesses include limited context awareness and more sophisticated techniques such as Lon Short Term Memory (LSTM) and Bidirectional Encoder Representations from Transformers (BERT, from Google) may improve results (Bell, 2020). In healthcare finance, Word2Vec has been used to provide personalised medication recommendations and predict health insurance fraud (Paliwal et al, 2022; Johnson and Khoshgoftaar, 2020).

Conclusions

All Health Finance Ltd is set to improve operations and increase returns by deploying AI in the three main areas of personalised insurance, data-driven investment advice, and AI customer assistants. Key potential problems include data protection and regulatory compliance, addressing errors and bias, and dealing with complexity in healthcare data. The approaches discussed for each area have their own strengths and weaknesses, and further research is needed to help select the most suitable strategies. This report represents the initial assessment for Senior Management to gain deeper understanding of the technical, legal and ethical issues brough up by deploying AI in AHF. Critical analysis of the essential concepts and techniques are presented alongside an effective plan for delivery of solutions to the business challenges.

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