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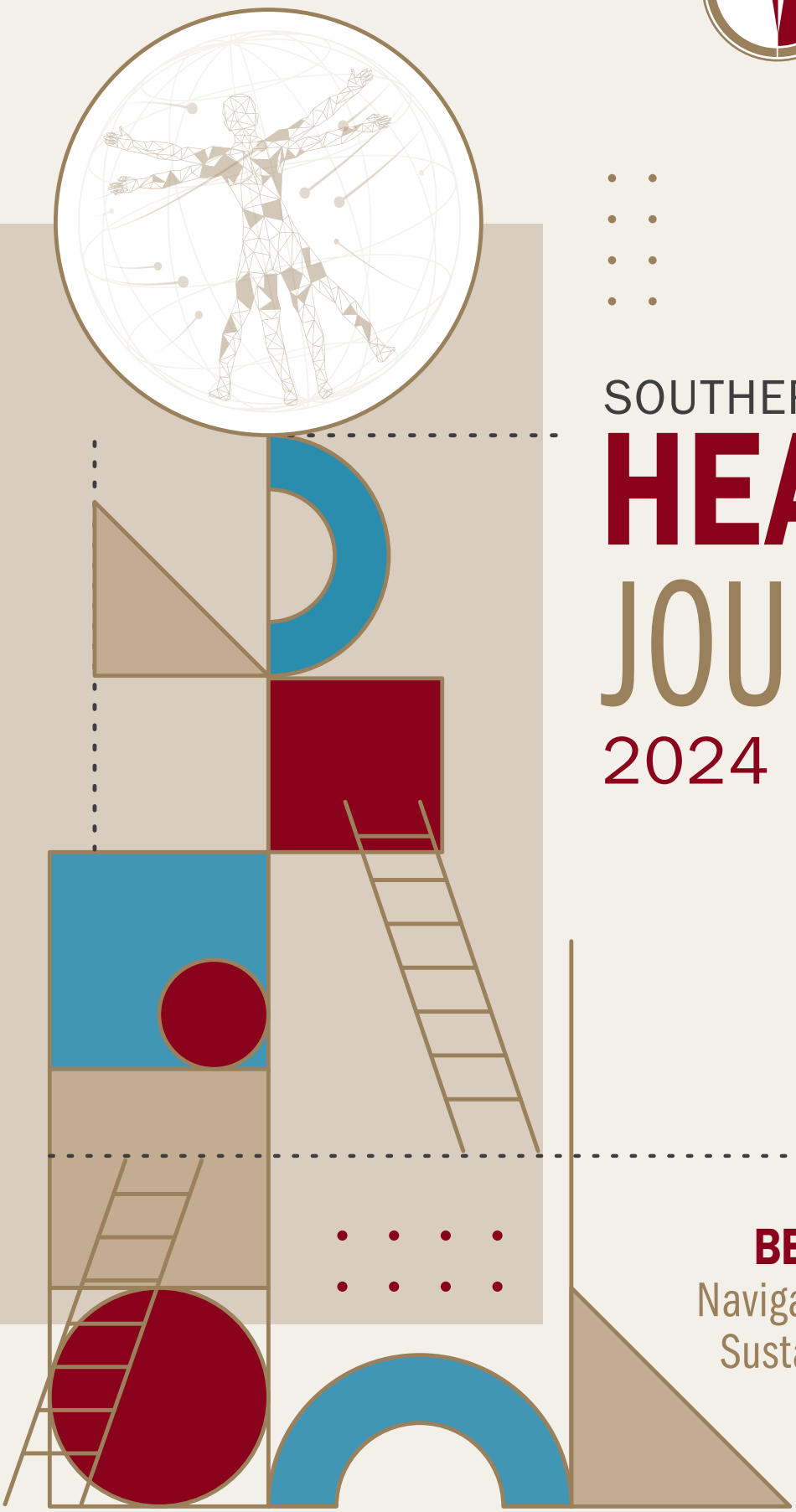

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BEYOND BARRIERS

Navigating the Future for Sustainable Healthcare

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From the EDITOR'S DESK

The Board of Healthcare Funders is pleased to present the fifth edition of the Southern African Health Journal.

This edition of the Southern Africa Health Journal focuses on improving the sustainability of healthcare systems. The papers included explore how healthcare systems can improve, increase access to and quality of care while maintaining affordability.

Most of the papers focus on how we can leverage advances in technology to improve sustainability. It is therefore no surprise that artificial intelligence (AI) and big data are tools commonly used in pursuit of this goal. One of the key papers focuses on governance frameworks around AI. This is important, as in most countries the regulations relating to AI are, at best, relatively immature or, at worst, non-existent. This paper provides a good tool kit for implementing AI initiatives in a health system.

Other papers highlight how we can leverage AI to improve care coordination in managing chronic patients, post-discharge patient monitoring and case management of high-risk patients. These papers highlight how patient outcomes are improved; at the same time the financial positions of health funders are improved as the number of episodes of care decline as intensity of care is reduced. Similarly, AI may be used to create access to more affordable eye-care at a primary level. Grant Newton argues that AI-based fundoscopy is accessible and allows for early detection of pathology, thus benefiting the health system.

Value-based care is key to sustainability. One of the papers reviews various components of the value-based care models implemented by a health funder in South Africa. It highlights successes and the main considerations for scaling value-based care.

Another way of improving sustainability is the extension of the shelf-life of medicines. A paper on this subject highlights some supply issues, including those related to the stocking of medicines. The recommended approach is cost effective and offers savings to funders while improving the availability of medicines.

The issues of an increasing disease burden and healthcare fraud, waste and abuse are addressed in two papers. One highlights the multi-dimensional nature of non-communicable diseases, focusing on mental health illness. This paper proposes a holistic approach to managing patients, rather than a silo approach focused solely on a specific diagnosis.

The other paper is an in-depth analysis of medical scheme claims data, highlighting areas of potential misuse of health services. Graham Hukins urges benefit designers to pay more attention to avoid misuse and abuse of health services.

We would like to thank all the authors for sharing their knowledge and all the peer reviewers for their hard work.

Charlton Murove
Head of Research, Board of Healthcare Funders

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AI GOVERNANCE:
Designing a Human-Centric Framework for Sustainable Healthcare in Africa

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PEER REVIEWER: Eunice Seekoe

EXECUTIVE SUMMARY

Background

Globally, artificial intelligence (AI) is transforming industries at a rapid pace, and healthcare is no exception. AI holds immense promise for revolutionising healthcare, reducing costs, increasing access, and benefiting professionals, patients and healthcare systems. However, there is reason for concern. The absence of effective AI governance increases the risks of adverse health outcomes, human rights infringements and technological power concentration.

If governments, policymakers, organisations and individuals work together to implement a human-centric AI governance framework, African countries will be able to navigate their way to sustainable and inclusive health systems. Globally there is a trend to follow a risk-based approach in AI regulation, underpinned by international standards and country-specific policy initiatives.

Methods and Assumptions

Comparative analyses and literature reviews were performed to measure the approach and key focus areas of international leaders with a sample of African countries. Policy recommendations of the World Health Organization (WHO), United Nations Educational, Scientific and Cultural Organization (UNESCO) and Organization for Economic Cooperation and Development (OECD) were assessed and a case study was undertaken that highlights the risks associated with unregulated AI usage, specifically focusing on the risk posed by behavioural psychology and psychographics, where the security of data privacy remains weak. The assumption is that the literature is up to date and that the principles are interpreted in a uniform way globally.

Limitations

Data sets of Africa are not consistent in respect of the countries and factors that were measured. African sources are limited, compared to other jurisdictions. The development of and research on effective regulation is not commensurate with the rapidly evolving field of technology.

INTRODUCTION

Data plays a fundamental role in self-determination in that it empowers individuals to make informed decisions and exercise control over their personal information. According to the Word Economic Forum (Hofmeyr, Wolf and Cloete, 2022), data has also become a commodity with the potential to contribute over $15 trillion to the global economy by 2030 (Frazier, Koerner, & Jones, 2023). From an African perspective, it is anticipated that AI can lead to the investment of $1.2 trillion in the African continent (Welle, 2023), which would contribute greatly to the achievement of the goals of the African Union's (AU) Agenda 2063.

With big data being the foundation of AI, Africa as the most genetically diverse continent on Earth (Achenbach, 2009), should be uniquely placed to benefit from AI. However, its lack of infrastructure, funding, resource capacities and digital expertise means that data is generated locally but not available or hosted locally. Consequently, the door is open for multinational technology companies to step into this void and monopolise the digital economy (World Health Forum, 2023). According to Principle 5 of the United Nations Global Compact, it further creates a risk that Africa's unique economic, social, heath, safety and cultural conditions will not be adequately represented in the design of AI systems.

PROBLEM STATEMENT AND PURPOSE

This paper underscores the critical role that governance plays in balancing the benefits of innovation with the interests of patients and the broader society.

According to Senegalese AI expert, Seydina Moussa Ndiaye (2024), the infiltration of multinational technology companies that mine Africa's data for AI development, represents a new form of 'digital colonisation' that sidelines local innovation and talent. This results in Africa potentially losing ownership of its intellectual property, with digital solutions that are not fit for the African context.

This paper sets out the characteristics of a trustworthy AI governance framework based on:

A. Global trends in AI regulation: determining to what extent existing legal frameworks can be used to regulate AI and how it can be enhanced by coordination and learnings from global leaders;

B. A human-centric approach: examining enablers and barriers to a human-centric approach; and

C. Navigating the way to sustainable healthcare: determining how these considerations can navigate the way to sustainable healthcare in Africa.

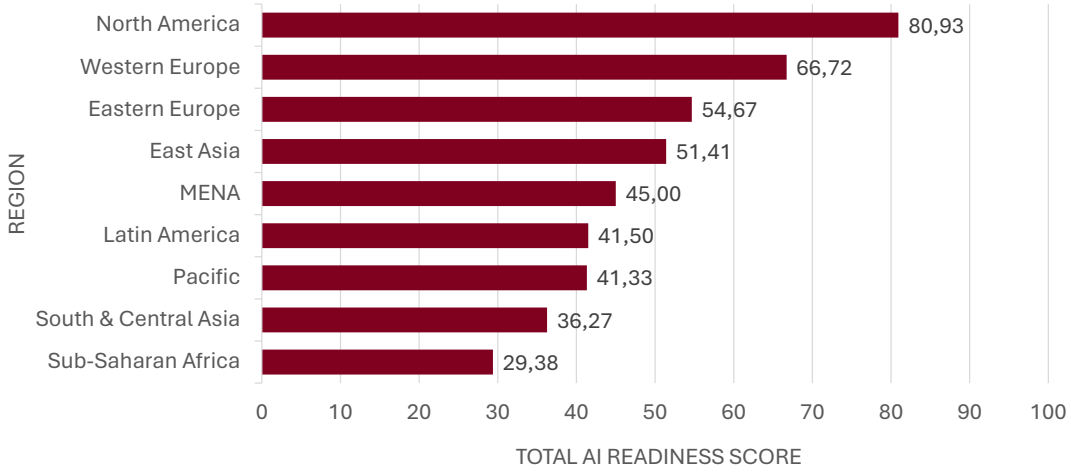
DISCUSSION AND RESULTS

A. Global trends in AI regulation

According to Gabriela Ramas, Assistant Director-General for Social and Human Sciences of UNESCO, governments around the world have decisively moved on from the question of whether to regulate AI to the urgent question of how.

The Government AI Readiness Index (Oxford Insights, 2023) evaluates countries and regions based on their technology, governance and data infrastructure relating to AI.

Figure 1. AI readiness per region

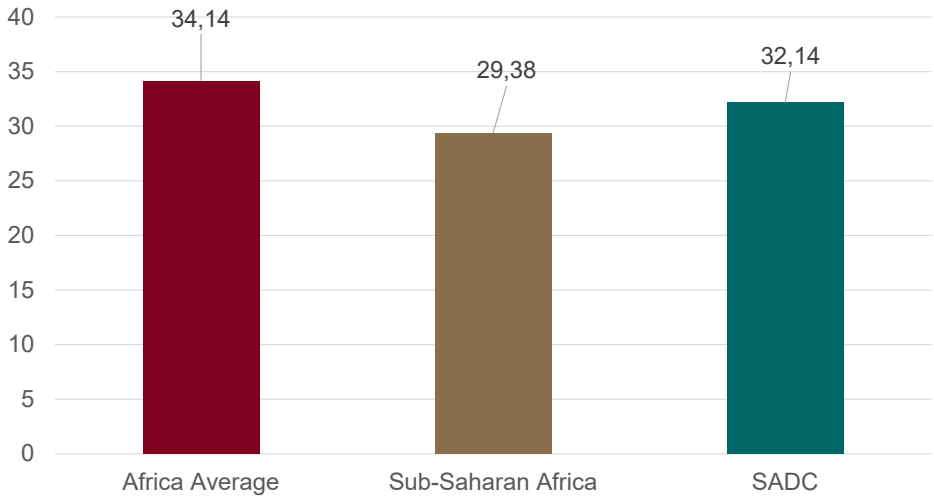


Regional results showed that North America had the highest score, with sub-Saharan Africa attaining the lowest score. According to the report, South Africa is the only country in sub-Saharan Africa that scored above the global average with regard to technology and data infrastructure, but its overall score was reduced by the governance pillar. This illustrates the need for the South African government to strengthen its policy initiatives with regards to AI.

Out of the 193 countries included in the study, the USA was ranked in first place, followed by Singapore and the UK. Mauritius was the highest scoring African country in 61st position, followed by South Africa in 77th place. The Democratic People's Republic of Korea obtained the lowest overall score.

When the data per continent, region and sub-region were extracted, the results for the African continent and Southern African Development Community (SADC) region ranked well below the global average.

Figure 2. African readiness score per continent, region and sub-region



The following observations were derived from the Index, the UNESCO AI Survey (Neupane and Sibal, 2021) and the AU continental strategy:

Table 1. Factors influencing AI readiness in Africa

Governance Pillar	Technology Pillar	Data and Infrastructure Pillar
• There has been an increase in published strategies and summits by middle- and low-income countries. • Only 10 African countries have national strategies (Neupane and Sibal, 2021). • Legal and governance frameworks need to be implemented and aligned across the continent.	• Various technological innovations have been deployed in Africa to strengthen health systems (WHO, 2021). • AI literacy, education and research must be advanced. • More than 300 million Africans live more than 50km from an internet connection. • Human capacity and investment costs are the main challenges (Neupane and Sibal, 2021).	•There is a significant digital divide between income groups and genders (where women are underrepresented). • 500 million people in sub-Saharan Africa do not have legal identification, resulting in the lack of digital IDs (Musoni, Domingo and Ogah, 2023). • Africa has 2144 languages (Achenbach, 2009), which can impact the training and use of AI models.

Comparing AI governance approaches

The International Association of Privacy Professionals' Global AI Law and Policy Tracker (Frazier,2023) and the OECD's AI Policy Observatory (2024) provides a comprehensive overview of the governance approaches per country. There is a correlation between the three most dominant geopolitical role players and the dominant regulatory approaches to digitisation and AI regulation (Hofmeyr, Wolf and Cloete, 2022).

Adopting international standards

In comparing the key features of the USA, Singapore, the EU and the AU it is reassuring to note the global adoption of ethical and governance principles. The OECD, UNESCO and UN AI Advisory Board all promote trustworthy AI that is centred around the furtherance of education, human rights and democratic values. The UN is advocating for governance by formalising it in international law. With regard to healthcare, the WHO (2021), promotes the adoption of:

- Autonomy and transparency, where humans understand and remain in control of healthcare decisions
- Wellbeing and inclusion that promotes access to healthcare and medicine
- Accountability for the safe and responsible design of AI by operators
- Sustainability to promote public health goals.

Following a risk-based approach

The EU is the first region to promulgate AI-specific legislation, the EU Artificial Intelligence Act (European Parliament and the Council of the European Union, 2024), which prescribes a risk-based approach. AI systems that have the potential to manipulate human behaviour and exploit vulnerable groups are categorised as unacceptable and banned under the Act. Medical devices and biometric devices fall under the high-risk category and are subject to stringent requirements, while chatbots are classified as low risk.

The US has taken a more flexible approach by proposing a voluntary AI risk management framework for organisations. The National Institute of Standards and Technology (NIST, 2023) AI Framework provides a process for governance, risk management, lifecycle management and stakeholder interaction. A new presidential executive order requires the licensing of high-risk AI systems, algorithmic impact assessments and the labelling of AI-generated content. Individuals must be notified when AI makes decisions that impact their rights and opportunities, and they must have the option to opt out of automated systems and select a human alternative (Dori, 2024).

Singapore, as the second-highest ranking country, implemented a model AI governance framework focusing mainly on the financial sector. It empowers companies by providing guides for job redesign, impact and self-assessments and governance testing toolkits.

China is in the 16th position and its concerns over the use of deepfakes inspired the regulation of generative AI, where all deep-synthesis algorithms must be registered with the government. A deepfake is a type of AI that create videos or images by misrepresenting or manipulating someone's face or voice. The state has control over all technology and uses AI for surveillance, censorship and social control. Consumers have the right to turn off algorithmic recommendations and to request explanations for AI impacts their interests.

According to Hofmeyr, Wolf and Cloete (2022), no AI-specific legislation or frameworks have been created in SADC countries or the broader AU. There are a number of regional initiatives like the AU's Continental Strategy on AI (2023); the Blueprint for African Member States in collaboration with Smart Africa Alliance; and SAFARI, comprising seven countries who adopted the UNESCO recommendations (2021). Mauritius established an AI council; South Africa has an AI institute and Botswana has an innovation hub. South Africa has launched pilot projects in schools, while some universities are facilitating projects between private and public stakeholders. Overall regulatory development in Africa is either to general to address AI or based on old technology (Townsend et. al, 2023).

The analysis shows that each jurisdiction has unique focus areas. However, South African and the broader African region are lagging behind in the implementation formal governance frameworks. The technology sector is driven by the private sector without proactive government support.

> Studies published by the National Institutes of Health and the WHO indicate that there are 15 African countries that do not have any form of data protection legislation yet (Musoni, 2024). There is therefore also a need for global alignment on privacy practices.

Incorporating AI in existing legal frameworks

AI has a significant impact on data protection, cybersecurity, intellectual property, competition, consumer protection and healthcare laws (Townsend et.al, 2023).

Daniele Solove (2024) did an in-depth study of artificial intelligence and privacy and found that current laws fall significantly short in addressing the regulation of AI in the absence of AI specific legislation. As an example, data protection legislation like the Protection of Personal Information Act (POPIA) in South Africa and the General Data Protection Regulation (GDPR) of the UK provide a data subject with the right to correct their personal information or withdraw their consent for the processing thereof at any time. However, once that information is included in an AI system it becomes basically impossible to extract it from an AI algorithm informed by a large data set. Privacy practitioners are also not necessarily AI or technology experts. While the GDPR and POPIA do not protect personal information in the public domain, the Health Insurance Portability and Accountability Act (HIPAA) in the USA does. Studies published by the National Institutes of Health and the WHO indicate that there are 15 African countries that do not have any form of data protection legislation yet (Musoni, 2024). There is therefore also a need for global alignment on privacy practices.

In two separate cases, US courts found that only humans can create intellectual property (Thaler v. Register of Copyrights and Director of the United States Copyright Office, 2023) and that secret algorithms that are used to manipulate market data are anti-competitive (Picchi, 2023). An example is that of a marketing company, Cambridge Analytica, which was shut down after a US Senate Judiciary Committee hearing regarding the sourcing of individuals' data from social media giant, Facebook. The hearing shed light on how Cambridge Analytica exploited insights on people's personal information to target specific demographics with misinformation, potentially influencing the 2016 US presidential election outcome. The hearing also highlighted the need for vigilance in safeguarding data privacy and preventing similar scenarios in the future. Facebook owner Meta agreed to pay $725m to settle legal action over the data breach linked to Cambridge Analytica (McCallum, 2022). The fact that the marketing company itself was not found to have violated any law shows that there are gaps in even the most advanced jurisdictions. Globally the adjudication of AI-related disputes is novel, and there is limited legal precedent.

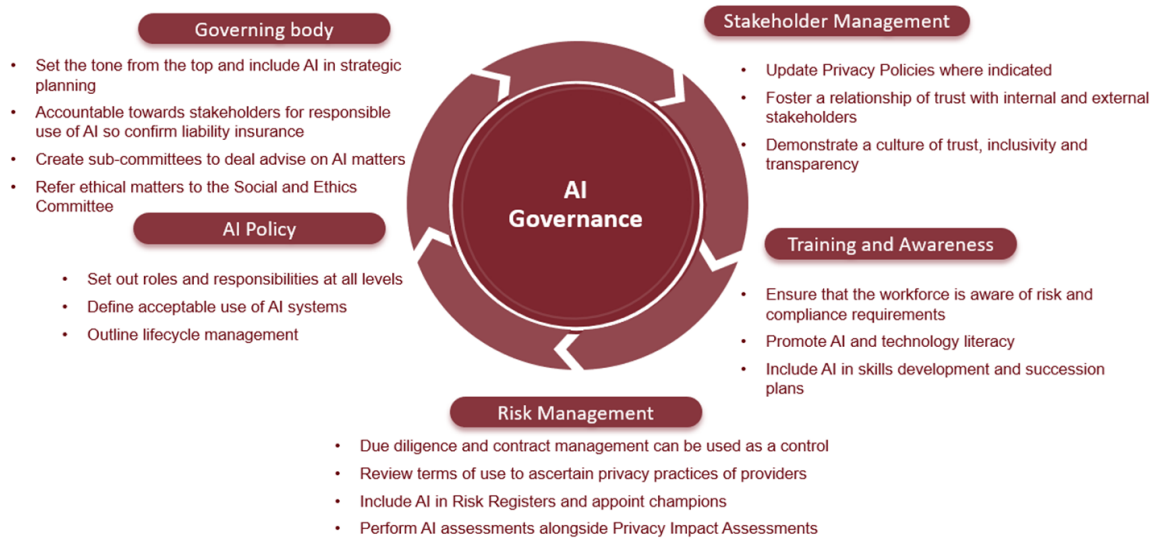
To conclude this topic, medical devices, telemedicine, product liability and the like are regulated to a certain extent in some but not all countries. However, it is not sufficient to cover the novel and rapidly evolving features of AI and policymakers will have to evaluate all the affected disciplines of the law.

Promoting AI governance in organisations

Governing bodies of organisations are accountable for the responsible use of AI. The King IV report on corporate governance does not expressly address AI but its outcomes-based principles are broad enough and aligned with that of trustworthy AI to serve as an interim guideline. Existing frameworks must be evaluated and amended or supplemented with AI-specific requirements.

When employees use AI tools for work, be it to generate text, automate processes or do research, it can lead to the unintended disclosure of personal information or trade secrets. Depending on the terms of reference of the specific tool, the company's intellectual property and cybersecurity may be at risk. It is therefore imperative that organisations equip their workforce with AI literacy, guidance and skills to ensure safety and consumer trust. Organisations can start with the following basic steps (Figure 3):

Figure 3: Proposed governance considerations for organisations



B. A human-centric approach

Human autonomy

Human-centric AI is based on the design and use of AI in a manner that enhances human capabilities instead of replacing them. It concerns itself with the mental and physical wellbeing of patients and guards against the manipulation and abuse of human cognitive biases that can undermine the principles of human autonomy and control.

Informed consent and data privacy

The South African Health Market Inquiry Report (2019)[1] found that consumers are disempowered to make appropriate decisions about their healthcare needs. Benefits, treatments options, algorithms and the contractual terms of AI applications may all be too complex for the average individual to fully comprehend. Furthermore, AI algorithms transcend simple data collection and generate new data about a person by scraping content from online platforms. Platforms like Zoom, Google and X (formerly Twitter) updated their privacy policies to allow for the processing of data to train AI models, but users are probably unaware of the implications of their acceptance thereof. Solove (2024) therefore contends that lawmakers should better control AI generation instead of leaving humans in control of their own data.

Transparency and explainability

AI systems must be designed in consultation with developers, patients, medical professionals and regulators so that all stakeholders understand how they work and specific decisions are reached. Doctors must be able to explain AI interventions to patients and they must in turn be empowered to appeal automated decisions if they are not satisfied with the outcome.

[1] *Investigation into private healthcare in terms of Chapter 4A of the Competition Act of 1998*

Case study

The Cambridge Analytica case referred to earlier illustrates the ability of AI to influence people to alter their behaviour towards outcomes that suited the marketing firm's clients' interests.

With access to the right information, AI-driven algorithms are able to output information, misinformation or disinformation that, when paired with messaging personalised by individual psychographic segmentation, can modify individuals' decisions. Understanding this risk starts with understanding how we as humans make decisions, health-related and otherwise, and what has changed in the world of AI to allow these levels of manipulation.

The Dual Process Theory of decision-making described by Kahneman proposes that humans have two distinct systems for making decisions (Kahneman, 2011). The one is the 'Thinking Fast system' characterised as fast, automatic and intuitive. This system operates unconsciously and relies on heuristics, biases and past experiences to make quick judgments and decisions. Think of this as 'intuition' or 'gut feel'.

The other is the 'Thinking Slow system', characterised as slow, deliberate and analytical. This system is responsible for conscious reasoning, logical thinking and effortful processing of information. Think of this as the 'reasoning' or 'calculating' brain.

Our analytical and logical Thinking Slow system is limited in its capacity and can easily be overwhelmed, leaving us to rely on our Thinking Fast system for most automatic and routine decisions. This phenomenon of making intuitive decisions over calculated decisions is what lends our decisions to being influenced or 'nudged'.

The concept of nudging is not a novelty of modern marketing; it draws on more than a century of research in the fields of psychology and sociology. What distinguishes nudging from other behavioural approaches to decision-making is its distinctive methodology, which incorporates behavioural insights (BIs) and libertarian paternalism (LP) (Marteau, 2011).

BIs leverage findings from behavioural and social psychology that elucidate why individuals occasionally make choices that defy conventional economic rationality. LP aligns with the concept of guiding individuals (paternalism) toward decisions that enhance their well-being while preserving their autonomy (libertarian) to opt for alternative courses of action.

The importance of these two concepts, BIs and LP, is that together they allow for nudging to provide neat solutions for influencing the more powerful and consistent Thinking Fast (intuitive) system but within the bounds of paternalistic guidance that best serves our individual interest. The authors of Nudge, Thaler and Sunstein, argue that ethics are not transgressed in nudging as no choice is taken away from individuals (Thaler, 2009). However, if LP is unbundled, as it can be with many AI algorithms, BI has the potential to promote the interests of the 'nudger' over those of the individual.

Nudging specifically influences key areas involved in independent decision-making (Figure 4 on page 12), confounding the question of ethical transgression.

The advent of three modern technologies have significantly enhanced behavioural insights, allowing for extremely powerful and highly personalised nudges to be developed. These technologies are big data accumulation, cost-effective high-performance computing and open-source machine-learning libraries.

The rapid development of these BI-enhancing digital technologies has outstripped the pace of development of the LP aspect of the nudging methodology to the extent that it has become unbundled.

Figure 3: Proposed governance considerations for organisations

Dr Alexander Tayler (2018), Chief Data Officer of Cambridge Analytica, discussed the company's use of big data and psychographics in the communications industry.

Cambridge Analytica built detailed profiles of individuals by combining various data sources. They collected information from third-party providers, social media platforms and their own proprietary sources to create a psychographic analysis from thousands of data points for millions of individuals (Tayler, 2018). This included detailed information on individual personality types, emotional insights and thinking styles. By analysing these data with machine learning, they could accurately predict individual behaviours and preferences.

With this comprehensive, segmented picture of its audience, Cambridge Analytica could nuance its messaging accordingly (Tayler, 2018). Adapting the right messaging method to the right psychographic profile, they were able to nudge individuals enough to change their behaviour. Unable to distinguish between interaction with an AI system or a human, targeted individuals made decisions in a manner that may not have aligned with their interests in all instances.

UNESCO recommends that its member states must develop guidelines for human-robot relationships with special attention to the mental and physical health of human beings. Patients must be able to easily identify if they are interacting with a human or an AI system like a chatbot and they should have the right to insist on a human intervention.

Algorithmic fairness and bias

"AI algorithms will emphasise the cultural practices and behaviours of the people whose data it is trained on" (Solove, 2024). If input data is biased, then outputs will be biased, and the unique features of economically disadvantaged populations and racial minorities will be underrepresented in algorithms depending on the availability and quality of data. As an example, it would be difficult predict diagnoses or provide individualised care plans for these groups.

UNESCO and the WHO (2021, p.70) stress the importance of setting up safeguards for the vetting of algorithms by experts. In Africa, special consideration must be given to the inclusion of women and any other marginalised groups through the entire AI lifecycle.

Safety and accountability

AI must only be used under appropriate conditions and by appropriately trained people. "Responsibility can be assured by application of 'human warranty', which implies evaluation by patients and clinicians in the development and deployment of AI technologies." (WHO, 2021, p 13.) A good example is IBM's Watson for Oncology which reportedly provided unsafe and incorrect recommendations for cancer treatment due an unrepresented data set.

Providers may be faced with changes or increases in medical malpractice and liability insurance due to the risks posed by novel AI interventions. Various AI models use 'black box technology', where internal workings are not displayed to the user and the provider will have to justify why they supported machine-generated recommendations.

C. Navigating the way to sustainable healthcare

The African Union's Health Strategy (2016-2030) aims to achieve a digitally enabled health system where access to affordable high-speed internet will promote health outcomes, access to healthcare in remote areas and put patients in control of their own health data. Sustainability is also concerned with the retraining and upskilling of the health workforce to prevent job losses and the appropriate disposal of digital devices. The WHO indicates that climate change will have a significant impact on healthcare in the future (2021, p. 80).

AI can aid in the achievement of the Sustainability Development Goals relating to healthcare (Babarinde et.al, 2023), provided that all citizens are able to access and gainfully use it. Access to hospitals and specialists, improved efficiencies brought on by automation and increased diagnostic accuracy are just a few of the benefits associated with the deployment of AI in the healthcare system. From a funding perspective virtual access can increase provider networks and access to specialists. Chatbots can empower patients with information about costs, formularies, medical scheme benefits, eligibility criteria and rules at any given time. Further efficiencies in administration and managed care can drive down non- healthcare expenditure and operational costs of funders and allow them to focus on personalised care.

Forward-looking regulations should provide reporting and audit requirements to assess the effectiveness and environmental impact of AI in healthcare and keep governments and organisations accountable. Tax incentives can also promote eco-designs, energy efficiency and extended use of medical technology.

CONCLUSION AND RECOMMENDATIONS

Humans are instrumental in AI innovation. Instead of focusing on the regulation of technology, we should be focusing on the humans who regulate, develop, train and use the technology informing AI models.[2] Existing frameworks must be aligned and there must be greater collaboration between different role-players. Effective, human-centric governance models promote human autonomy and prevent harm through a risk-based approach. Policymakers, especially in Africa, need to act with urgency to create appropriate guardrails to protect and advance human rights. Organisations should likewise position themselves to remain competitive and set the tone for human-centric AI governance.

AI must be governed by and for humanity.

[2] *Professor Emma Ruttkamp-Bloem. Ethics Alive Symposium. April 2024*

APPENDIX: KEY CONCEPTS

The following table aims to provide non-technical readers with an understanding of the terms used throughout the paper.

Artificial intelligence	Machines acting like humans by performing complex tasks with accuracy and without human intervention.	
	Generative AI	Computer models capable of generating novel content like chatbots interacting with members in a call centre.
	Machine learning (ML)	Technologies and algorithms that enable systems to identify patterns, make decisions and improve themselves through experience. ML can be used to predict hospitalisation trends.
AI governance framework	A set of laws, regulations, policies, and practices on national and organisational levels that ensure that AI operates in a manner that is ethical, fair, transparent and compliant.	
Big data	Large amounts of data collected from various sources at a rapid pace. This can include claims processed by funders or data collected from wearable devices.	
Human-centric	An inclusive and transparent approach focused on the needs and in the interest of the patient where the healthcare provider ultimately makes the decision.	
Psychographics	The study of patients or consumers based on their psychological characteristics and traits. The data can be used to nudge a person to act in a certain way and can be used for good (healthcare compliance) or bad (manipulating decisions).	
Sustainability	Providing quality health outcomes for current and future generations by considering the impact of technology on the environment and the labour market.	

You can use this QR Code to access the IAPP's Glossary of Terms for AI Governance

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AI-DRIVEN HEALTH CONCIERGE: Optimisation of Healthcare Services for Greater Population Impact

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EXECUTIVE SUMMARY

In South Africa, 5% of medical scheme individuals account for approximately 51% of healthcare spend and 46% of healthcare administrative services. The disproportionate nature of healthcare expenditure can be partly explained by the hospicentric illness-focused healthcare model utilised by the health system, which leads to expensive episodic care that manages the most urgent risk in the moment. In keeping with the aim of primary healthcare and universal health coverage, whole- of-life-prevention focused and coordinated healthcare is required to manage health needs and cost.

Care coordination is not a new concept in health. A recent publication by PWC (Dr Jenkins, Deas, & Mehrfar, 2023) highlighted that globally this is being implemented with various degrees of success. One of the biggest challenges is how to deliver care coordination at scale to individuals who have complex healthcare needs. One example of a solution offered for this problem is the approach of the Gulf Cooperation Council (GCC) countries (including KSA, UAE and Qatar) in digitising care coordination through artificial intelligence (AI) and big data to deliver cost-effective and superior health outcomes for the entire continuum of care. So, the question is how we use AI and data to deliver care coordination to the entire population with various needs, wants and barriers to health management in an African context.

One proposed solution is to package care coordination into an AI-predictive driven solution that coordinates, manages and optimises the complete lifetime health journey of certain individuals within the population and delivers the greatest impact.

INTRODUCTION

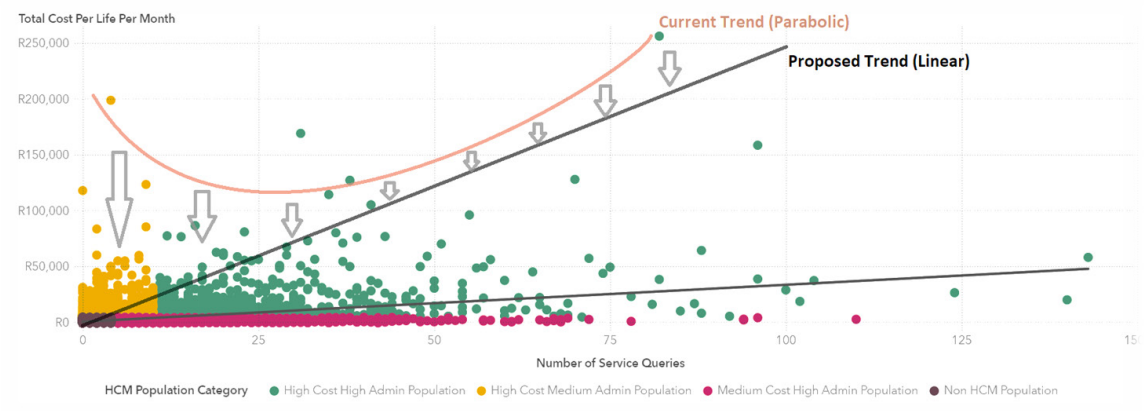
Care coordination in healthcare is a critical factor that influences both the cost and outcomes of patient care. It involves the deliberate organisation of patient activities and information-sharing among all stakeholders concerned with a patient's care to achieve safer and more appropriate care. Effective care coordination has been shown to improve healthcare efficiency and safety, leading to better patient outcomes. For instance, it can help eliminate disjointed care within healthcare systems, reduce unnecessary hospitalisations, repeated tests, conflicting prescriptions, and ensure clearer communication between providers and patients about the best treatment.

Effective care coordination is pivotal in enhancing patient outcomes. Recent studies indicate that it substantially diminishes the likelihood of 30-day readmissions, mortality rates and healthcare expenditures for individuals (Chang & Tung, 2024). Elevated levels of care coordination correlate with reduced 30-day readmission and mortality probabilities, alongside decreased costs in comparison to minimal care coordination (Snively, 2024). Moreover, it mitigates the incidence of redundant procedures, care fragmentation, medical errors, and care gaps, thereby augmenting patient satisfaction, involvement and self-management (Moriarty & Mugge, 2024). Additionally, it bolsters the dissemination of information among healthcare specialists, culminating in enhanced care quality (Healthstream, 2021) . Consequently, care coordination is integral to healthcare reform initiatives aimed at bolstering outcomes and curtailing expenses (Chang & Tung, 2024).

In assessing the role of care coordination in South Africa, we applied the Johns Hopkins ACG Care Density measures (Pollack, Lemke, Roberts, & Weiner, 2015) to determine its impact on healthcare costs, administration and outcomes. The analysis, further explained in appendix B, indicates that individuals with minimal care coordination incur, on average, 23% higher costs [N = 1 781 232; p-value = 0.021; CI (0.0872; 0.517830)] and experience 31% more service inquiries [N = 1 127 781; p-value = 0.000922; CI (0.0123; 0.4321112)] compared to those receiving extensive care coordination. These statistics underscore the significant effect of care coordination on essential facets of healthcare provision.

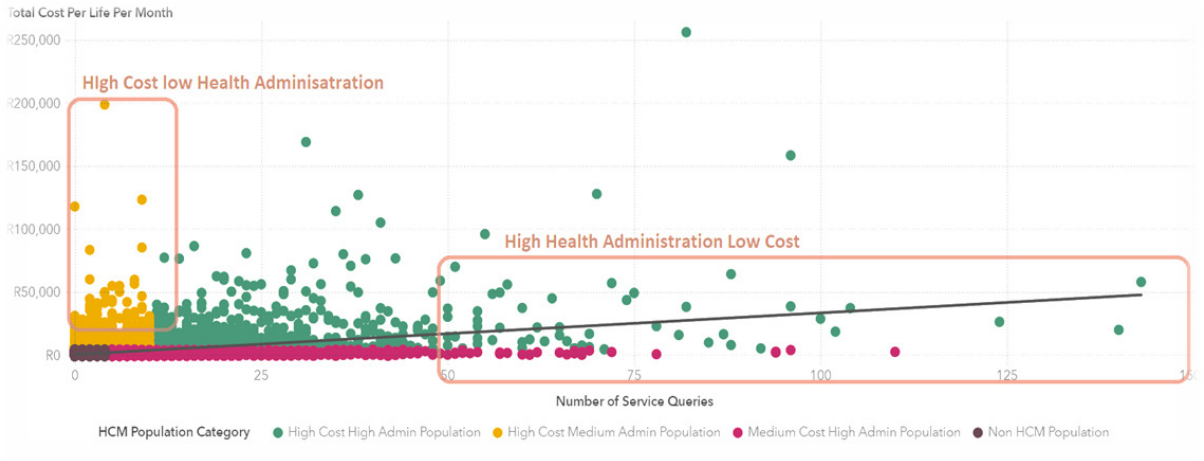
This study presents a health concierge model designed to optimise the uneven distribution of costs and resources, ensuring that those in dire need receive efficient care. The research indicates that approximately one-third of expenses and service inquiries stem from inadequate care coordination. A parabolic pattern emerges when plotting costs against health administration efforts (Figure 1).

Figure 1. Healthcare cost vs healthcare administration distribution (over a 12-month benefit year)



Individuals at the lower spectrum of health administration contribute disproportionately to costs, and the reverse is also true. The health concierge model aims to proactively pinpoint these individuals to prevent future imbalances in cost and administrative efforts. Ideally, a direct correlation between healthcare costs and administrative efforts would establish a more equitable distribution of resources, effectively neutralising the effects of care coordination discrepancies, as suggested by (Snively, 2024)(Figure 2).

Figure 2. Healthcare cost and administration groupings



It's important to distinguish the health concierge model from the concierge medicine model, which is known for its premium, membership-based services (Robinson-Walker & Hall, 2023) Unlike concierge medicine, the health concierge model is designed to streamline the healthcare delivery system, involving patients, healthcare providers and financiers. This ensures that care is tailored to the needs of the patients rather than their financial capacity. As a result, this model reshapes and redefines the dynamics among patients, healthcare providers and financiers.

The health concierge model thrives on the analysis of extensive data sets. For instance, a healthcare administrator might handle upwards of 12 million claim lines, 1.5 million inquiries and 475 000 calls each month. This translates into countless data interactions, offering a myriad of possible insights. Therefore, a healthcare funder embodies the traits of a big data entity, tasked with enhancing care delivery. The wealth of data available to the funder, and consequently to the health concierge model, enables the identification of key indicators that can elucidate, forecast and overcome obstacles in care coordination. This, in turn, influences healthcare costs and the management of population health. These insights allow for the crafting of tailored health journeys that directly address care coordination challenges. These journeys are designed to suggest the necessary healthcare interventions at each point along the care continuum. It's crucial to recognise that the AI within the health concierge model is designed to continuously learn and refine the interventions that are most effective for each individual's unique profile. In situations where a data-rich environment is lacking, these journeys serve as a model for deducing the required interventions for specific personas, offering a customised care plan when data is abundant and a strategic approach for population personas when it is scarce. This underscores the transformative potential of the health concierge model in personalising and optimising healthcare delivery.

METHODS

The mission of the health concierge model is to streamline the provision of healthcare within the ecosystem, ensuring that appropriate care is administered in the ideal environment for each person. Balancing the diverse goals of patients, healthcare providers and financiers presents a complex challenge. It involves leveraging the data available to financiers to anticipate and comprehend the present and prospective requirements of patients, aligning them with suitable services and providers. This alignment is crucial for reducing the administrative overheads associated with healthcare and enhancing the overall health results for the population.

The health concierge model integrates two primary components: the service model and the intelligence model. Together, they tackle the challenges of care coordination. The intelligence model leverages AI to generate insights and forecasts, which are then implemented and enhanced by the service model within the healthcare framework. This service model encompasses a network of people, actions, programmes, regulations and interventions, all aiming to streamline the delivery of healthcare to the targeted population. This includes roles like care coordinators, innovative payment structures (alternative reimbursement models), and health promotion programmes, including wellness. The strength of the health concierge model lies in its ability to merge these elements, optimising healthcare delivery by identifying and applying the most suitable intervention for an individual at the precise moment, catering to their present and prospective health requirements. Appendix D includes illustrations depicting the interaction between the two components (Figure 4) and outlines the prospective modifications in care delivery shown in Figure 5. This paper primarily concentrates on examining the intelligence layer and its various facets.

Intelligence layer

The complexity and individuality of healthcare delivery necessitate a personalised approach to effectively address each person's unique health challenges. Intelligence plays a pivotal role in providing insights and indicators for the population at large. Within the health concierge model, intelligence is categorised into stratification, personalisation and care coordination. Stratification aims to identify an individual's current and prospective health requirements. Personalisation delves into understanding an individual's specific circumstances, obstacles to accessing healthcare, and their preferences and expectations. Meanwhile, care coordination involves aligning an individual's needs with the appropriate health interventions to ensure optimal management and outcomes. This approach supports individuals in managing their health proactively and empowers them with the knowledge to navigate the healthcare system efficiently.

Stratification

Predictive algorithms are employed to categorise the population into manageable groups for coordinated care and health management services. The objective is to identify which segments of the population are likely to incur the highest healthcare costs and utilise the most resources. To achieve this, various models are utilised to forecast individual health outcomes and events, taking into account each person's present and past data. These forecasts can signal the probability of health declines or improvements, triggered by specific occurrences. For instance, these models can estimate the chances of a 45-year-old man being hospitalised for hypertension within the next year, based on his medical history and lifestyle patterns. These estimations are then refined by considering recent activities or event sequences, such as medical consultations, health risk evaluations or lifestyle changes like starting a fitness regimen.

The application of these risk stratification models has identified a specific segment of the population that requires comprehensive management to maximise overall benefits. The health concierge model effectively segments the population into four unique categories:

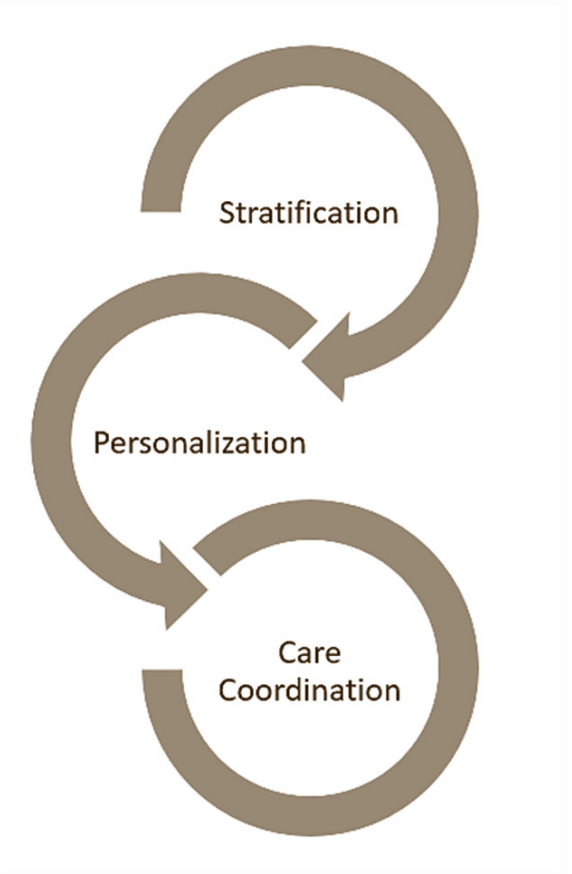
- Health concierge population: This group, representing a mere 6.7% of the population, accounts for 40.9% of healthcare administrative resources and 36.8% of healthcare costs. Optimising care for this segment could significantly influence the management of the broader population.
- Cost-skewed population: This population segment incurs higher costs than what is spent on healthcare administration.
- Service-skewed population: This segment utilises more healthcare administration services relative to their healthcare costs.
- Remaining population: This group is characterised by additional event-based indicators.

Consequently, intensive management of just 6.7% of the population has the potential to affect 40.9% of costs and 36.8% of healthcare administration. Moreover, this segment exhibits the lowest level of care coordination, with 53% indicated to have care coordination issues, as detailed in appendix E.

Personalisation

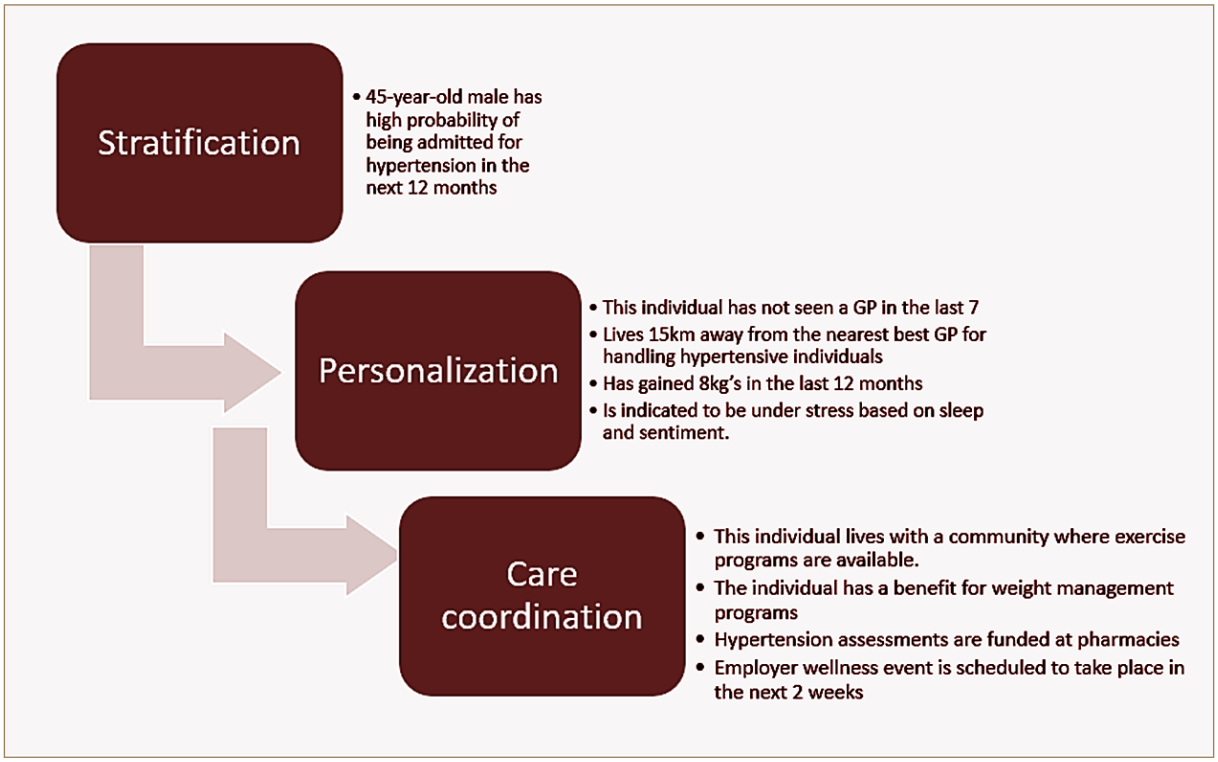
The intelligence layer's personalisation is designed to comprehend an individual by analysing not just their health data, but also their behaviours and preferences, which reveal their unique obstacles in care coordination. This approach utilises a comprehensive set of data that encompasses health, socio-economic factors, lifestyle and social interactions/media to construct an all-encompassing profile of the individual. The strength of this method lies in its ability to continuously understand an individual's life. It aims to develop distinct personas that help predict the effectiveness of interventions based on anticipated health events. For instance, the impact probability for an individual is tailored according to their specific persona. A critical aspect of this process is identifying the actionable barriers to care coordination. The accompanying diagram illustrates how the various layers interact (Figure 3).

Figure 3. Intelligence aspects



Care coordination

Care coordination serves as the foundational layer of intelligence, constructed upon AI models that align personas identified in the personalisation layer with health event predictions from the stratification layer. This alignment facilitates the implementation or suggestion of interventions, optimising the accuracy of predictions, personas and interventions to enhance the efficiency and effectiveness of healthcare delivery. Notably, this layer employs a blend of machine learning and multi-objective mathematical modelling to discover uniquely tailored combinations. These combinations, termed 'health concierge pathways', are customised for individuals based on available data or are extrapolated based on personas when individual data are limited. An illustrative example of these pathways is depicted in the diagram below. The primary advantage of this method is that it generates essential health concierge pathways recommendations, which can be disseminated to any participant in the healthcare delivery network. A comprehensive list of the care coordination models developed appears in Appendix E.



Each of these elements is beneficial in its own right for enhancing our comprehension of healthcare delivery. Yet, it is the distinctive amalgamation of stratification, personalisation and care coordination that equips us with the capability to actualise the envisioned health concierge model. The results of the models that support this solution can be found in appendix F.

CONCLUSION

This article suggests that the key to advancing effective healthcare lies in transforming health services through digital means and fostering integrated care. At the heart of this transformation is the implementation of AI within the healthcare system. The data presented highlight the promising capabilities of AI to improve healthcare services. However, the incorporation of such technologies comes with its own set of challenges, including technical, social, commercial and ethical concerns, which may cast doubt on their overall advantage across the healthcare spectrum. Additionally, the paper indicates that when data-centric solutions are seamlessly woven into the healthcare framework, they hold the promise of significantly reforming healthcare by refining the functions of all involved parties and improving the health outcomes for patients.

APPENDIX A

Evaluating machine-learning models' performance is a critical phase in the development process. Various metrics are available to assess a model's effectiveness, tailored to the specific problem, dataset and goals. Commonly utilised metrics include accuracy, precision, recall, F1-score, ROC curve, AUC, MSE, MAE and R2.

Accuracy represents the ratio of accurate predictions to total predictions made by a model. While straightforward and simple to apply, its reliability may falter in cases of unbalanced class distributions or non-binary issues.

Precision denotes the ratio of true positive predictions to all positive predictions made by a model, serving as an indicator of the model's exactness in pinpointing the positive class.

Recall measures the ratio of true-positive predictions to all actual positive cases, reflecting the model's ability to identify the positive class correctly.

The F1-score, as the harmonic mean of precision and recall, provides a consolidated measure that captures the model's balanced performance in terms of both metrics.

The ROC curve visually plots the balance between the model's true-positive rate and false-positive rate across varying thresholds, while the area under the curve (AUC), representing the area beneath the ROC curve, quantifies the model's capacity to differentiate between classes. A model is considered superior if it has a higher AUC value.

Mean squared error (MSE) quantifies the average of the squares of errors, essentially gauging the variance between observed and forecasted outcomes. Mean absolute error (MAE), on the other hand, calculates the average magnitude of errors in a set of predictions, without considering their direction. The coefficient of determination, denoted as R2, assesses the proportion of the variance in the dependent variable that is predictable from the independent variable(s), with a value of 1 indicating a perfect prediction.

In evaluating our model, we concentrate on metrics that reflect its predictive accuracy and reliability, specifically: Accuracy, which measures the proportion of correct predictions; the F1-score, which balances precision and recall; the Gini coefficient, which gauges inequality among values of a frequency distribution; and the AUC, reflecting the model's ability to distinguish between classes.

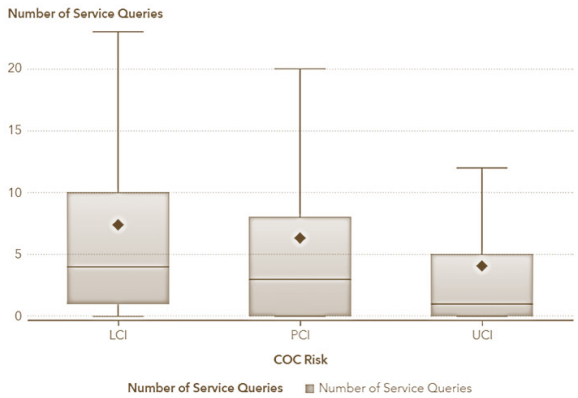
APPENDIX B

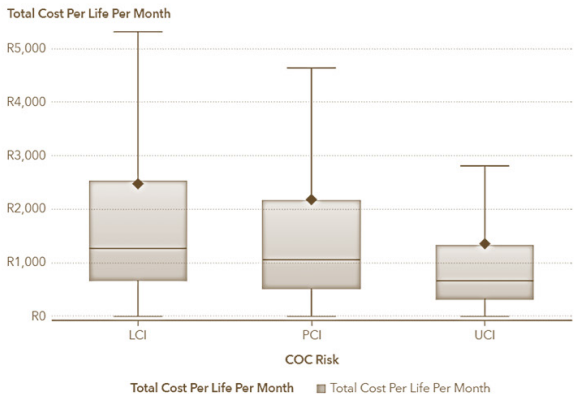
The Johns Hopkins ACG® System's care density metrics, referenced in (Pollack, Lemke, Roberts, & Weiner, 2015), serve as a surrogate for evaluating care coordination. This concept, termed 'Care Density', is predicated on the hypothesis from research conducted at the Johns Hopkins Bloomberg School of Public Health, which posits that increased patient-sharing among clinicians correlates with enhanced communication and information exchange. Studies have shown that a deeper insight into patient-sharing patterns among healthcare providers can lead to decreased hospitalisation rates and cost savings. Notable research includes that (Pollack, Lemke, Roberts, & Weiner, 2015) the relationship between care density and healthcare costs and (Pollack, Lemke, Roberts, & Weiner, 2015) on the impact of patient sharing on care quality.

The ACG System quantifies this aspect of patient care through the 'Care Density Score', a patient-specific metric reflecting the extent of shared care among clinicians. In a recent study utilising 2023 data encompassing 2 813 672 individuals, we analysed the correlation between care density levels and healthcare costs, including administrative service inquiries. The study categorised care density into three levels:

- LCI (Likely Care Coordination Issue) indicating minimal care coordination,
- PCI (Partial Care Coordination Issue) denoting partial coordination, and
- UCI (Unlikely Care Coordination Issue) representing high levels of care coordination.

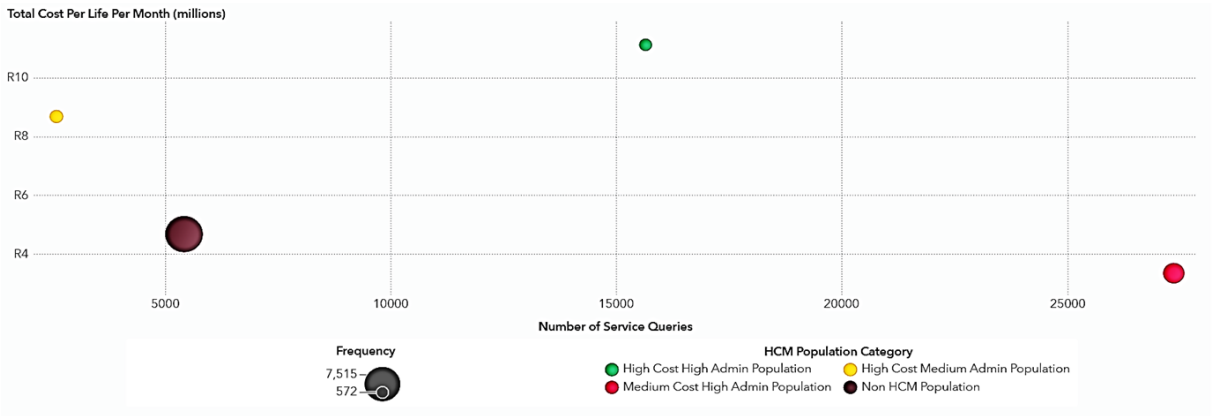
We risk-adjusted this population using a combination of factors including age, gender and chronicity to yield the following results for our primary measures of cost per life per month and number of service queries. These results showed that individuals who had minimal care coordination (after risk adjustment) have 23% higher cost [N = 1 781 232; p-value = 0.021; CI (0.0872;0.517830)] and 31% higher service queries [N = 1 127 781; p-value = 0.000922; CI (0.0123; 0.4321112)] when compared to individuals who had a high level of care coordination.





APPENDIX C

By analysing the private medical scheme population for a 12-month benefit year focusing on their healthcare cost spend and health administration burden. The results below are from the application of the proposed health concierge model in terms of grouping individuals based on their healthcare resource needs and administration burden.



APPENDIX D

The health concierge programme is designed to align patient needs with healthcare services efficiently through an algorithmic method emphasising care coordination. This shift aims to evolve the current fragmented and complex healthcare service model into an integrated ecosystem. At the heart of this ecosystem, the health concierge model orchestrates care delivery, managing not just isolated incidents but the entire continuum of patient care.

This coordination is made possible by the health concierge model's utilisation of data on individuals and providers to anticipate and meet the community's present and future health requirements. The model is built on three pillars: intelligence (data capability), integration (technology and resource enablement) and interventions (care coordination capability).

This paper specifically concentrates on the intelligence aspect of the model.

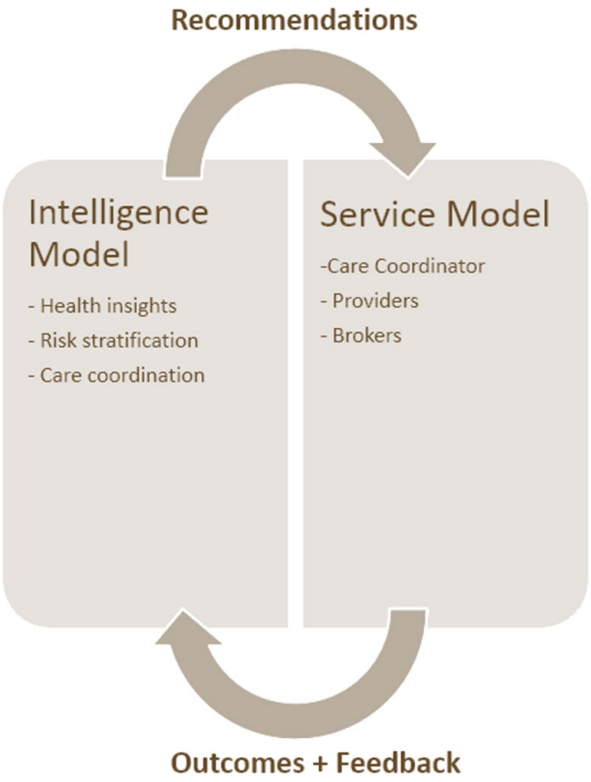
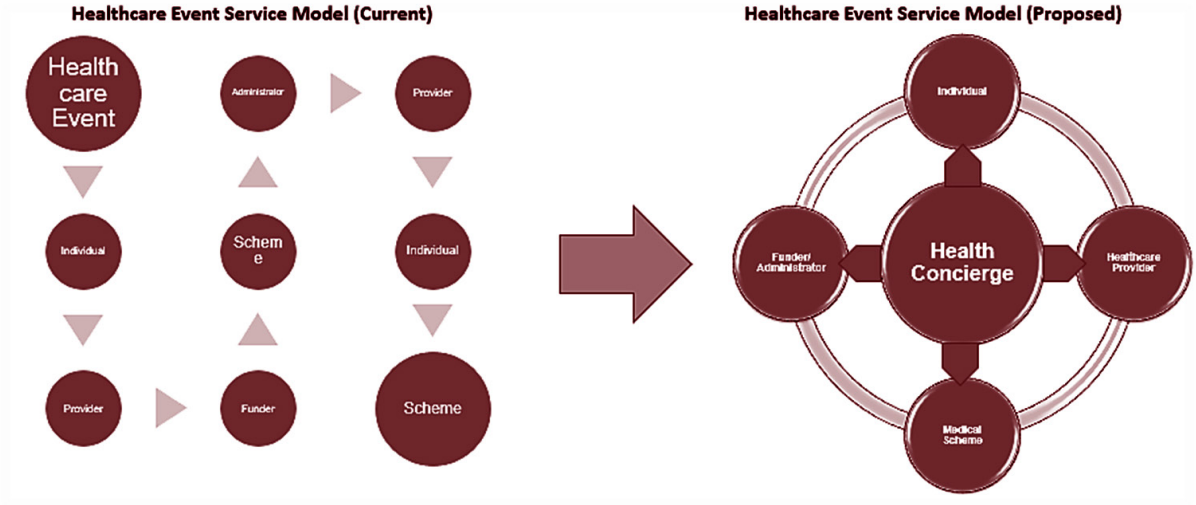


Figure 4. Interaction between the health concierge intelligence model and the service model.

Figure 5. Proposed change to the healthcare delivery ecosystem



APPENDIX E

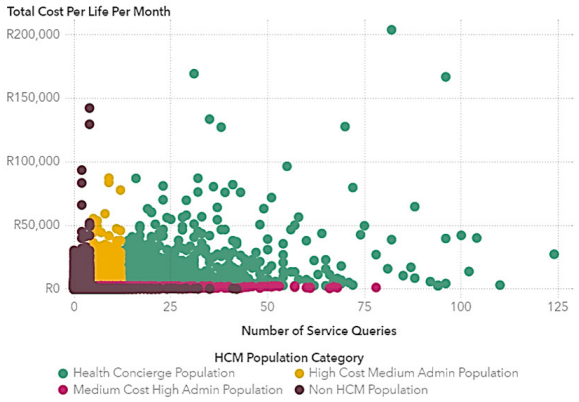
Identification of population by the health concierge model

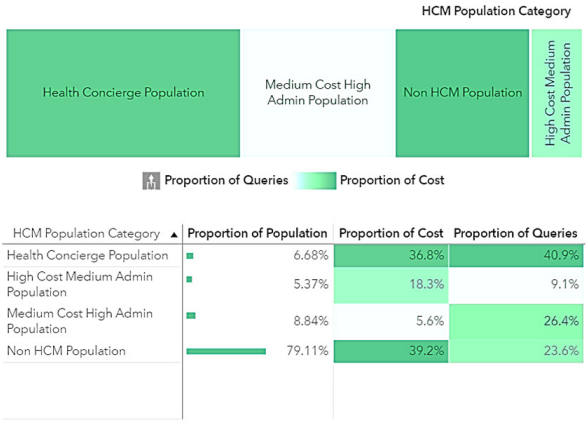
The categorisation models are an amalgamation of machine-learning methodologies, tailored to discern the unique attributes of an individual and align them with an optimal healthcare trajectory, thus crafting a personalised health journey across the continuum of care. The models include:

- High-risk utilisation: Forecasts the likelihood of individuals ranking in the top 15% for healthcare cost utilisation over the coming year.
- High-service utilisation: Estimates the probability of individuals being in the highest 15% for health administration utilisation in the upcoming year.
- Life stage clustering: Assesses the chances of individuals exhibiting characteristics that deviate from their expected life stage and health profile.
- Emerging needs models: Projects the healthcare requirements of an individual for the next year and up to three years.

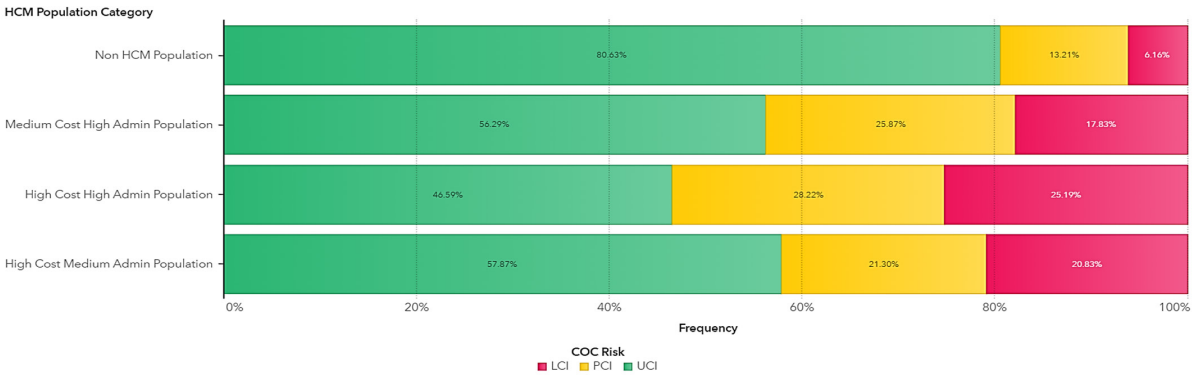
Healthcare needs assessment: Evaluates and categorises the current healthcare necessities of an individual.

Regular application of these models to the population ensures precise classification of individuals, addressing both present and prospective healthcare needs. This facilitates timely interventions and the coordination of requisite services. The insights gleaned are utilised by care coordination intelligence to proactively align suitable interventions with individual needs. This proactive strategy transforms the healthcare delivery model from reactive to anticipatory, with health concierge agents initiating care actions rather than responding to health events. The following is a concise overview of the models employed in the care coordination intelligence framework (Bukuluki, et al., 2023).





HCM Population Category	Proportion of Population	Proportion of Cost	Proportion of Queries
Health Concierge Population	6.68%	36.8%	40.9%
High Cost Medium Admin Population	5.37%	18.3%	9.1%
Medium Cost High Admin Population	8.84%	5.6%	26.4%
Non HCM Population	79.11%	39.2%	23.6%



Care coordination models built to facilitate the identification of health concierge pathways:

- Health episode prediction models
- Care pathway adherence models
- Service enablement models
- Primary care facilitation models
- Acute event management models
- Life stage management models
- Optimal provider models
- Health behaviour models
- Healthcare delivery barrier classifications
- Healthcare product optimisation

APPENDIX F

Model results

The effectiveness of the health concierge model hinges on its ability to provide digital care coordination, which not only reduces overall healthcare delivery costs but also enhances the system's efficiency. To thoroughly appraise the health concierge model, it is essential to examine both the intelligence and interventions, individually and in unison. This paper focuses predominantly on determining the precision and suitability of the intelligence for stratification, as well as its capability to furnish pertinent information for digital care coordination. At this juncture, our emphasis is on the comparative accuracy of these foundational models.

The significance of model information to the health concierge necessitates adherence to the model measurement framework delineated in Appendix A. Presented here is an encapsulation of the principal model measurements for the previously described models. The displayed results stem from an evaluation of data spanning 2021-2023, segmented into three classifications: training dataset (80%), testing dataset (10%) and validation dataset (10%). The outcomes for the validation dataset suggest that the models have performed commendably during testing and have achieved an acceptable accuracy level for implementation, in line with the performance of other machine learning models in the healthcare sector (Saad & al., 2020).

Intelligence Area: Stratification

Model	Model Description	Model Type	AUC	F1 Score	Accuracy
High-Risk Utilisation	Prediction of individuals that fall within the 85th percentile of healthcare cost utilisation in the next 12 months	Supervised	82%	56%	87%
High-Service Utilisation	Prediction of individuals that fall within the 85th percentile of health administration utilisation in the next 12 months	Supervised	78%	62%	81%
Life stage Clustering	Prediction of the likelihood of the individuals exhibiting characteristics not clustered in their life stage and health profile	Unsupervised		85%	
Emerging Needs Models	Prediction of the 12- month and 3-year healthcare needs of the individual	Supervised	66%	51%	63%
Healthcare Needs Assessment	Prediction and classification of the current healthcare needs of the individual	Supervised	79%	82%	89%

The findings suggest that the risk stratification models are quite successful in dividing the population and forecasting their health requirements. The subsequent phase involves assessing the efficacy of the combined care coordination models. This assessment, however, is contingent upon the measurement of the effects of the interventions implemented following the guidance of the health concierge model, in tandem with the intervention delivery model. Consequently, the forthcoming segment of this report will focus on examining how the health concierge is integrated into the healthcare system.

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Revolutionising Chronic Care Management WITH AI TECHNOLOGY

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EXECUTIVE SUMMARY

Background: Chronically ill patients account for 70-80% of medical scheme claims. Studies reveal that around 20.7% of South Africans suffer from multimorbidities, which include conditions such as diabetes, cardiovascular conditions and respiratory disorders. The absence of an automated and intelligently driven CMCC platform in this population results in non-compliance and 'care fragmentation', escalating the 'total disease burden' and healthcare expenditure.

Objective: To demonstrate the potential use of AI-enabled platforms in managing and coordinating the care of chronically ill members, thus reducing hospitalisations and optimising costs.

Methodology: For these studies, conducted in India and South Africa, we utilised a patient-centric AI-enabled platform incorporating a proprietary risk stratification algorithm to generate a unique risk profile (URP) for each individual. Determining the URP involves the calculation of a disease severity index (DSI), which categorises individuals based on their expected 'healthcare resource consumption'. The platform's impact on health outcomes, such as hospitalisation rates and the associated costs, was evaluated for cohorts sampled from ultra-high-risk (UHR) individuals. The South African study included a cohort of 35 000 randomly selected UHR individuals from a leading South African medical scheme.

Results: The South African programme's initial results are expected by September 2025. However, a similar initiative in India, among UHR individuals, led to an approximately 10% reduction in healthcare costs by lowering hospitalisation rates by 15%.

Conclusion: Adopting AI-enabled CMCC platforms offers a promising approach to the management of chronic diseases, aiming to improve patient outcomes and reduce healthcare costs. We hope to replicate India's success in the South African programme, further supporting the efficiencies obtained through the platform's adoption.

INTRODUCTION

Chronic diseases are conditions of long duration and slow progression, including both non-communicable diseases (NCDs) and communicable diseases (World Health Organization, 2002; 2016). In South Africa, NCDs account for 57.8% of all deaths, with 60% being premature (less than 70 years of age) (South African Medical Association, 2019). The predominant causes of NCD deaths include cardiovascular conditions, diabetes and respiratory disorders (World Health Organization, 2023). Over a 20-year period, from 1997 to 2018, the deaths from these NCDs in South Africa increased by 58.7% (Maluleke, 2023). The leading risk factor for cardiovascular diseases is hypertension; for respiratory disorders, it's chronic obstructive pulmonary disease and asthma (Maluleke, 2023).

Research from Free State province shows that 24% of the population suffers from chronic diseases (Lebina et al, 2020), and a study in Cape Town found that multi-morbidity prevalence is about 23%, with chronic diseases accounting for 45% of all primary healthcare (PHC) consultations (Oni et al, 2015). In 2021, South Africa saw its overall healthcare expenditure by medical schemes rise to ZAR205 billion, a 14.50% increase from 2020 (ZAR179 billion) (CMS, 2023). Patients with multiple chronic conditions frequently use healthcare services (Bell et al, 2022; Frølich et al. 2019; Prior et al, 2021). If not managed properly, they could increase hospitalisations and readmissions, both of which directly increase healthcare costs for medical schemes.

Effective and proactive management of these chronic disease patients is essential, necessitating strategies for automatic tracking and monitoring of patients' conditions outside the hospital setting to prevent potential hospitalisation and complications. This paper introduces an innovative approach utilising an AI-enabled platform designed to facilitate and coordinate care for chronic patients outside hospital settings, thereby tackling the dual challenges of managing NCDs and surging healthcare expenditure in South Africa's private sector. By leveraging AI to personalise care and reduce unnecessary hospital visits, this initiative seeks to lower costs and enhance patient outcomes.

REVIEW OF DISEASE RISK MANAGEMENT (DRM) PROGRAMMES

To reduce healthcare costs and alleviate the strain on health systems, medical schemes throughout South Africa have launched disease risk management (DRM) programmes to manage NCDs. These schemes have established internal care management teams and appointed DRM consultants responsible for monitoring and managing the risk of NCDs among beneficiaries. The consultants proactively contact beneficiaries diagnosed with one or more NCDs to assess their health status. However, through our direct work with specific medical schemes in South Africa, we have observed that this initiative exhibits significant inefficiencies and limitations for several reasons:

(a) The process lacks a systemic approach, relying entirely on manual operations.

(b) There is an absence of a mechanism for continuously identifying and categorising beneficiaries based on their expected healthcare resource consumption. Although the DRM consultants perform initial risk assessments when enrolling beneficiaries into the programme, the process lacks a systematic, continuous, event-triggered re-evaluation for updating risk categorisation.

(c) Beneficiaries diagnosed with a single NCD or multiple NCDs receive limited follow-ups, usually 2-3 per year; however, those with multiple NCDs require more frequent monitoring and follow-ups due to their increased likelihood of higher utilisation of healthcare resources.

(d) Although DRM consultants possess clinical knowledge, they often lack the specialised expertise required to proactively identify deviations in a beneficiary's expected care journey.

(e) The schemes currently lack a precise mechanism for identifying whom to connect with, when to connect, and what specific content to discuss during each interaction.

(f) Without assigning specific consultants to individual beneficiaries, multiple consultants may contact the same beneficiary regarding different NCDs, leading to disjointed communication, care instructions and data recording, resulting in fragmented care ultimately leading to confusion among beneficiaries.

(g) Managing beneficiaries' health effectively requires a substantial number of DRM consultants to cover all enrolled beneficiaries.

(h) Given the manual nature of the work, consultants can only reach out to 10-12 beneficiaries daily.

(i) The extensive DRM workforce required to run the operations significantly increases the operational cost, threatening the programme's sustainability.

PROPOSED SOLUTION

To address the complex needs of managing NCDs at scale and the shortcomings of current internal care management approaches, we propose the implementation of an AI-enabled CMCC platform. Unlike traditional software or manual processes, the AI-driven platform offers predictive analytics, adaptability and a personalised care approach critical for meeting the dynamic and diverse needs of individuals with NCDs. This AI-driven methodology enables medical schemes to analyse vast datasets, accurately predict health outcomes and create personalised care plans through continuous risk assessment for more effective optimisation of resource allocation.

A testament to the platform's potential and effectiveness is the success of a similar initiative previously conducted in India. The programme targeted an UHR cohort of approximately 45 000 beneficiaries with diabetes, obesity, cardiovascular and respiratory disorders, aiming to reduce hospitalisation risk throughout the financial year 2022-2023. Before initiating the programme, the baseline analysis for the previous financial year showed a 26% hospitalisation rate, accounting for 11 700 hospitalisations/claims at an average hospitalisation cost of ZAR36 324.

After a year of the DRM programme, results indicated a significant reduction in hospitalisation rates and average cost of hospitalisation - a 15.2% decline to 9 922 hospitalisations. The average cost declined by 9.3% to ZAR32 920. These improvements yielded more than eightfold returns for the medical scheme in one year.

Drawing upon the successful application of the CMCC platform in India, we anticipate a similar transformative impact on managing NCDs in South Africa, given the similar challenges both countries face.

Key features of the AI-enabled CMCC platform include:

(a) Integrated care plans tailored to each NCD, detailing expected complications, necessary gold standard laboratory tests, recommended physician visit schedules, lifestyle recommendations and education support on do's and don'ts, aiming for comprehensive disease management.

(b) The ability to assign beneficiaries to a specific consultant for personalised care.

(c) Implementation of adaptive machine-learning algorithms to determine whom to connect, when to connect and for what purpose to connect, so that the CMCC process is made easier, more efficient and more effective for DRM consultants.

(d) Hyper-personalisation of content: At every touchpoint, content is tailored using generative AI to match the beneficiary's NCD and risk profile, ensuring interactions are relevant and aligned with the beneficiary's health objectives.

(e) Adoption of a 'whole person model' to minimise member confusion: The CMCC platform considers all the NCDs of a beneficiary and develops a comprehensive care plan, which is then assigned to a single consultant for management. This approach streamlines care by consolidating all care needs into one touchpoint and addresses the confusion caused by disparate communications from multiple DRM consultants for different NCDs for the same beneficiary.

(f) Driving the compliance requirements for all the disease conditions on a single touchpoint: The platform proactively supports compliance by clearly presenting key elements of health management, including essential laboratory tests for each NCD, the required number of physician consultations for the year ahead, the prescribed medication details, advised lifestyle changes and dietary guidelines specific to each NCD. This functionality allows DRM consultants to review these components with beneficiaries, monitor adherence and encourage compliance with their treatment plans.

(g) Continuous risk re-evaluation and automated care plan adjustments: After every interaction, the platform automatically updates the beneficiary's risk profile and adjusts the care plans using machine-learning algorithms. This ensures that care plans immediately align with the beneficiary's most recent health information, enhancing health outcomes.

(h) Enhanced DRM consultants' expertise and streamlined operational efficiency: The efficiency introduced through the suite of advanced functionalities enhances the productivity of DRM consultants, enabling them to extend their daily outreach to 50-60 beneficiaries, thereby improving their productivity by at least 50%, consequently optimising operational costs and fostering a sustainable framework for chronic disease management.

IMPLEMENTATION FRAMEWORK

The essential prerequisites for the programme's success included:

(a) Data collection: The data required for developing a holistic beneficiary profile encompass age, gender, chronic conditions, hospitalisation history over the last two years, family health history, education qualifications, work type, lifestyle and social determinants of health (SDOH). This clinical and demographic information can be obtained from medical schemes' beneficiaries' records and historical claims data. The SDOH information is collected from the beneficiary at enrolment. Given that they may not always provide complete information during enrolment, the system's design allows for the collection of additional information at any subsequent interaction. To ensure comprehensive data collection and the successful implementation of the CMCC platform, integrating the platform into existing healthcare data infrastructure is strongly recommended to overcome challenges such as adapting to different healthcare IT systems, ensuring data privacy and security, and effectively training resources. However, if integration is not feasible for the Medical Schemes, the platform can still function effectively by allowing for manual input of data from Excel or PDF files that contain member details.

(b) Baseline estimation: Prior to initiating the programme, comprehensive baseline metrics are established using one-year historical data from the year immediately preceding the pilot, covering all the beneficiaries of the medical scheme. These metrics include incidence rate of hospitalisations, average cost of hospitalisation and average length of stay.

(c) Technology utilisation: Deploying an AI-enabled CMCC platform.

(d) Human resources: Engaging DRM consultants.

(e) Data analysis and risk stratification: Using the beneficiaries' demographics, medical history and SDOH data, the platform generates a URP for every individual. This profiling involves calculating a DSI, which serves as a predictive tool for healthcare resource consumption, thereby stratifying beneficiaries into UHR, rising-risk (RR) and low-risk (LR) cohorts.

(f) Care coordination and risk management: The platform uses the aforementioned whole person model of care to develop a personalised, comprehensive care plan for each beneficiary, spanning single or multiple NCDs, to address identified risks and effectively manage disease severity.

(g) Measuring impact: Upon concluding the initial pilot period, the programme's impact is assessed by measuring the incidence rate of hospitalisation, average cost of hospitalisation and the average length of stay for all intervened cases during the pilot period. In this context, 'intervened cases' refers to beneficiaries engaged through the platform by DRM consultants. The difference between post-pilot metrics and the baseline estimates determines the programme's impact and return on investment.

RESULTS

A nationwide programme was implemented in collaboration with a leading medical scheme in South Africa. This initiative, involving approximately 35 000 UHR beneficiaries diagnosed with NCDs, is designed to effectively coordinate care and proactively manage risks, aiming to reduce the rate of hospitalisation. The comprehensive review of the programme's outcomes is scheduled for September 2025. Based on the platform's proven success in India, we expect similar positive results in South Africa, specifically in reducing hospitalisation rates, lowering healthcare costs and enhancing the overall quality of care for beneficiaries with NCDs.

CONCLUSION

Worldwide, healthcare resource consumption related to chronic diseases is escalating year on year, and South Africa is no exception. The increasing burden of chronic diseases necessitates innovative solutions with a forward-thinking approach, simplifying the CMCC process. A business-to-business Software as a Service (SaaS) platform that uses generative AI and adaptive machine-learning helps care management teams handle at-risk beneficiaries through evidence-based behavioural interventions. These platforms adopt a whole person model to reduce member confusion and care fragmentation. By providing personalised, integrated care, the platform has the potential to significantly reduce the unnecessary healthcare costs associated with UHR cohorts by 10-15% for medical schemes and enhance member satisfaction through improved health outcomes.

As we stand on the brink of a new era in healthcare, embracing AI-enabled platforms for chronic disease management not only offers a pathway to substantially lower healthcare expenditures and improved patient care, but also signifies a pivotal shift towards more resilient, efficient and patient-centric healthcare systems. The encouraging outcomes of these technologies underscore their potential to redefine healthcare dynamics, compelling stakeholders to embrace these advances.

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INTEGRATING AI-BASED Mobile Fundoscopy into Primary Healthcare

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EXECUTIVE SUMMARY

The exigencies of healthcare today present a stark dichotomy — ever-growing patient needs juxtaposed against the limitations of available resources. Artificial intelligence (AI) is poised to catalyse a crucial shift in primary care delivery within this context. The premise of this study is driven by an acute challenge: to decentralise baseline diagnostics from specialists to primary care practitioners underpinned by AI technology.

Globally, the healthcare sector is grappling with a crisis of accessibility and affordability, particularly in specialist-led diagnostic services. These services often serve as gatekeepers to patient care, creating an unsustainable economic burden and limiting patient access (Global Health Care Outlook, Deloitte, 2021). The localised aspect of this crisis reflects the pressing need for legislative and procedural reforms that endorse the proficiency of AI-empowered primary care providers.

This study employs a comparative framework building on findings in Newton (2023), presenting a solid case to support the view that access to diagnostic care lies beyond patients' reach due to cost and access. It considers options from the literature that propose that these limitations can be overcome by empowering primary care clinicians with the tools supported by AI solutions. We seek to contrast AI-driven diagnostics within the primary care setting against conventional specialist-led diagnostic methods.

This comparison is grounded in a review of the existing literature that underscores the efficacy and efficiency of AI in primary care.

INTRODUCTION

Newton (2023) showed that clinical-grade technologies supported by proven AI help reduce primary care costs. We synthesise these findings with literature that builds on the notions in Newton (2023), Topol (2019 and Blease, et al (2019), among others, which demonstrate that AI algorithms, when used in primary care, can match or surpass the diagnostic accuracy of specialists for specific conditions.

The synthesis reveals that AI implementation in primary care can reduce costs by diminishing the need for specialist referrals and diagnostic testing (Blease, et al, 2019). The approach provides an understanding of the potential that AI holds in transforming diagnostic practices, paving the way for a more efficient and accessible primary healthcare system than the current one, which is fraught with challenges, including inequitable access and high cost vexing the rollout of universal health coverage in South Africa (Heunis, et al, 2019; Tediosi, et al, 2020). We also incorporate qualitative assessments of example AI technologies (more specifically AI-supported fundoscopy) sanctioned by regulatory authorities like the US Food and Drug Administration, which has approved AI systems for detecting conditions such as diabetic retinopathy with a sensitivity and specificity surpassing human clinicians (FDA Approves AI Device to Detect Diabetic Retinopathy, FDA News Release, 2018).

This study endeavours to map the trajectory towards a healthcare system where primary care is empowered with AI to democratise essential and critical diagnostic roles typically performed by specialists and tertiary care facilities. Highlighting the intersection of policy, technology and clinical practice, this paper seeks to inform and empower healthcare leaders planning the rollout of National Health Insurance and the private sector with options that make diagnostics pain-free, cost-effective and ubiquitous. To this end, we echo the sentiment of the World Health Organization's Director-General, Dr Tedros Adhanom Ghebreyesus, who stated: "Harnessing the power of digital technologies is essential for achieving universal health coverage (World Health Assembly, 2018)." This should be seen as a challenge to decision-makers to recognise and act upon the transformative potential of AI in primary care, thus enhancing the sustainability and efficacy of our health systems.

The primary healthcare system is unattractive to new graduates as it is under unprecedented strain, grappling with challenges such as the disenfranchisement of primary care doctors, limited remuneration, forced deployment and limited resources for essential diagnostics and patient care (World Health Organization, 2020; Gumede, et al, 2021). These challenges are juxtaposed with the high costs and universal access associated with specialist consultations and diagnostics. The South African Health Market Inquiry (HMI), whose findings were released in 2019, resolved that the concentration of specialists is hospicentric and that they are concentrated in provincial capitals and metropolitan areas, often resulting in limited access to primary care diagnostics like routine diabetic retinopathy screening (Hudson-Lamb, 2022). When patients are referred to specialists for baseline screening, we find that inflated healthcare expenses deter them from pursuing essential diagnostic examinations informed by international guidelines (Yuyun, et al, 2020).

This practice not only incurs additional costs but also undermines the role of primary health workers (Bhat, et al, 2023). Access to specialists is limited and expensive, preventing patients from obtaining the critically necessary basic screenings. Specialists have been enabled to take over procedures traditionally performed by general family practitioners (GPs). The latter must search for alternative revenue streams to sustain their practices. This shift can lead to over-servicing, where GPs are forced to perform unnecessary services to compensate for lost income. The economic burden of this practice leaves patients and insurers bearing the brunt of inflated costs without corresponding improvements in patient outcomes (Bafghi, et al, 2020). Kaplan et al (2020) show a redundancy in care when specialists perform services that fall within the primary care purview, emphasising the need for a more collaborative healthcare model that optimises resource utilisation and maintains the financial viability of GPs (Corradetti, et al, 2024).

The challenge of specialist dependency and cost implications

In addressing the issue of specialist dependency within healthcare systems, it is essential to consider the allocation of basic diagnostic screenings. The current paradigm, where specialists are the primary providers of essential diagnostic services like fundoscopy, increases healthcare costs and decreases patient accessibility (Vujosevic, et al, 2020). This is not a sustainable practice and emphasises the inefficiencies caused by bottlenecks in healthcare delivery (Rao, et al, 2021). Similarly, Grzybowski and Brona (2021) show that the financial burden of specialist-based screenings contributes to escalating healthcare expenses, which can become prohibitive for both patients and payors.

We reference the systematic literature review on diabetic retinopathy access in sub-Sahara Africa, where Achigbu et al (2023) highlight the diabetes epidemic and, more, its impact on increasing blindness in this population. Achigbu, et al (2023) have shown that limited access to DR screening can be attributed to reasons of cost, restricted equity and access, education and awareness and an endemic design flaw in public and private benefit designs and protocols. If the public and private sectors adjust benefits to democratise diagnostics and incentivise primary care visits for wellness and vital diagnostic screenings, it will reduce costs and promote what Gu, et al (2024) show, i.e. that fundus screenings in primary care can serve as the first line of defence in detecting systemic diseases. This is supported by Malerbi, et al (2022), who show that handheld or mobile fundoscopy integration in primary care is a prime example of empowering primary care providers to conduct appropriate, ubiquitous, thorough and efficient screenings, facilitating the early detection of conditions that could otherwise lead to severe complications if left unchecked.

Can the primary health system absorb the burden of primary diagnostic screening?

Schwarz, et al (2022) show that the high costs associated with diagnostics wrapped in specialist consultations reduce the likelihood of patients seeking necessary preventive measures and screenings, such as fundus examinations, essential for detecting eye diseases like diabetic retinopathy or age-related macular degeneration. While these economic barriers to accessing such screenings can result in poorer health outcomes and higher long-term costs both for individuals and the healthcare system (Wang, et al, 2021), we must explore whether primary care systems can absorb this responsibility.

The ongoing strain on the primary healthcare system is a multifaceted problem that has significant implications for the sustainability of healthcare delivery and the overall well-being of populations. The World Health Organization highlighted this issue in 2019, pointing to the acute shortage of primary healthcare professionals. This shortage is more than just a matter of numbers; it also reflects a broader issue of the maldistribution of healthcare workers, which exacerbates health disparities between regions (Williamson, 2023). Shanafelt, et al (2022) also raise the issue that primary care doctors systematically increase low-paying workloads to maintain sustainability, heightening an economic imbalance in a system serviced by GPs and specialists.

This disenfranchisement and scurry for revenue for primary care doctors often manifests in overservicing. With the increasing complexity of care and the need for multidisciplinary approaches, primary care doctors may feel marginalised, undervalued and underpaid, notably when their role is diminished in favour of specialist care (Babenko, 2018). In many cases, the consequent overservicing, along with the need for diagnostic tools and their reimbursement, results in undesirable referral patterns to specialists for uncomplicated screening. While specialists are crucial for complex cases, an overdependence on them can create unnecessary pathology. When this occurs, more tests and procedures are ordered than clinically indicated, which can lead to overdiagnosis and overtreatment (Babenko, 2018).

AI in redefining diagnostic screening

AI technology is poised to redefine diagnostic screening by providing non-invasive, accurate and cost-effective alternatives to traditional methods, such as blood-based diagnostics (Arya, et al, 2023). Adopting AI in diagnostic processes introduces standardisation and objectivity, reducing variability and improving the accuracy of disease detection (Park and Han, 2018). This shift has the potential to significantly impact public health by facilitating early detection and intervention, ultimately reducing the overall burden of disease management (Subramanian, et al, 2020).

AI plays a transformative role in advancing diagnostic screening. AI-driven technologies are innovating how we detect diseases, with implications for healthcare services' efficiency, accuracy and reach. AI applications in diagnostics, particularly in imaging, have exhibited remarkable capabilities in identifying pathologies previously dependent on more invasive methods like blood draws (Haick and Tang, 2021).

The power of AI lies in its ability to learn and recognise complex patterns within vast datasets, including medical images. This capacity not only introduces a high degree of precision but also reduces the incidence of human error, thus standardising the diagnostic process.

Exampling AI-based mobile fundoscopy: a solution for primary healthcare

The advent of AI in healthcare has heralded a new era in the early detection and management of systemic diseases, including cardiovascular and neurological disorders (Patil and Shankar, 2023). To address the conundrum highlighted above, we specifically examine the pivotal role of AI-based mobile fundoscopy in empowering primary healthcare systems, focusing on its impact on reducing costs and enhancing the accessibility of diagnostic and clinical services for systemic diseases in primary care settings. We look at how we can capacitate and empower primary care clinicians and increase the capacity and viability of this professional segment.

By leveraging the retinal vasculature as a window to systemic health, AI algorithms can analyse fundoscopic images to identify biomarkers indicative of systemic conditions such as hypertension, diabetic retinopathy and even signs correlating with neurological diseases like Alzheimer's (Khan, et al, 2023; Tan and Sun, 2023; Schmidt-Erfurth, et-al, 2018; Heger and Waldstein, 2024). Integrating AI in medical diagnostics has been a game-changer, particularly with technologies like AI-based mobile fundoscopy. This innovative approach not only streamlines the diagnostic process but also significantly enhances the accessibility and affordability of care. Schmidt-Erfurth, et al (2018) have demonstrated that these portable devices, coupled with advanced AI algorithms, can immediately analyse retinal images, detecting conditions such as diabetic retinopathy, macular degeneration and other systemic diseases with impressive accuracy.

Hristova, et al, (2021) have shown that AI-based mobile fundoscopy is highly accessible to primary care physicians and other paramedical primary care clinicians. It requires minimal training to use effectively, given that the AI component of the system carries the burden of complex analysis typically reserved for specialists (Sosale, 2019). Primary care settings, often the first point of contact for patients, can thus become hubs for preventive screening, utilising these devices to identify risk factors or early signs of diseases. For instance, Gilbert and Sun (2017) found that non-specialist personnel could use these devices to capture images that AI could evaluate with a precision comparable to that of expert specialists.

Literature underscores that the mobility of fundoscopy devices and the ease of operation at paramedical levels enables the extension of these diagnostic capabilities to remote and underserved populations, addressing significant disparities in healthcare access (Kumar and Paul, 2023). The cost-effectiveness of this approach is further highlighted by studies showing that early detection through AI-based screenings can increase access

and substantially reduce healthcare expenditures by curtailing the need for expensive specialist care (Chaki, et al, 2022).

Incorporating AI-based mobile fundoscopy into primary healthcare settings streamlines the patient care pathway by enabling primary care providers to conduct initial screenings. It facilitates timely referrals, ensuring early intervention for systemic diseases (Betzler, Rim and Sabanayagam, 2022). This integration is poised to transform the management of chronic conditions, offering a proactive model of care that prioritises prevention and early detection.

The availability of such technology in a primary care setting has profound implications. We can democratise early diagnosis and intervention capability, improving patient outcomes and using both primary and specialist healthcare resources more efficiently. It allows for decentralisation of healthcare, where sophisticated diagnostics can be performed in community clinics, rural doctors' offices or even mobile health units, making it especially beneficial in underserved areas.

Furthermore, mobile fundoscopy units' portability and ease of use make them ideal for integration into existing healthcare practices (Yu, Beam and Kohane, 2018). They are cost-effective in reducing the need for patients to have multiple appointments with different providers, avoiding the duplication of tests, thus conserving healthcare resources. With the proper infrastructure and support, these devices can be widely distributed and maintained, making AI-based diagnostic screening a standard component of primary healthcare services.

Horton, et al (2020) highlight the ability of this technology to be seamlessly integrated into community pharmacies, where pharmacies can serve a dual purpose by screening and referring to GPs as necessary. Decentralising diagnostic services through AI-based mobile fundoscopy reduces costs and helps ensure equitable access. Essential healthcare screenings can be provided in rural areas, as well as to underserved communities and populations with limited access to care.

The expansiveness of AI-based mobile fundoscopy is also evident in its potential for telemedicine applications. Patients can be screened in remote locations, with images being analysed by the AI and reviewed by doctors as necessary, bridging geographical and accessibility gaps in healthcare provision.

Overall, AI-based mobile fundoscopy is a powerful tool that aligns with the broader goals of modern healthcare: enhancing access, reducing costs and providing high-quality care. Its deployment across various platforms exemplifies the innovation that illustrates a step forward in preventive medicine and the early detection of disease.

It allows for decentralisation of healthcare, where sophisticated diagnostics can be performed in community clinics, rural doctors' offices or even mobile health units, making it especially beneficial in underserved areas.

CONCLUSION

In a world where health equity remains challenging, AI, specifically AI linked to fundoscopy-sourced retinal images, is a key player in levelling the playing field, offering opportunities for high-quality diagnostic capabilities irrespective of geographical and socio-economic barriers. AI based Fundoscopy, democratises healthcare by enabling early and accurate screenings in various settings — from rural clinics to urban wellness programmes — and ensuring that all patients receive the care they need, regardless of their circumstances.

AI-based mobile fundoscopy represents a pivotal advance in healthcare technology with its vast potential for widespread application. The walls of traditional medical institutions do not constrain this modality; instead, it can be easily incorporated into diverse settings, fundamentally transforming the approach to preventive healthcare and screening.

Employers and occupational health clinics can deploy it by integrating fundoscopic exams into regular health check-ups. Companies can monitor the well-being of their workforce, potentially catching systemic health issues and referring them to formal treatment, which can lead to early detection and a significant minimisation of downstream complications.

Moreover, mobile fundoscopy units' portability and ease of use make them ideal for mobile diagnostic assessments. Health providers can bring these devices directly to communities, enabling them to conduct large-scale screening events efficiently. Wellness days and health fairs often serve as an individual's first encounter with health education and screening, and by incorporating AI-based fundoscopy, these events can offer a more comprehensive assessment of an individual's health.

This discussion thread has woven a narrative that underscores the responsibility of payors, policymakers and healthcare providers to come together to support this technology. It's not merely about deploying sophisticated tools, but the concerted effort to train and empower primary care clinicians to use them effectively. In this synergy, we find the heart of a transformed healthcare system: proactive, patient-centric and efficient.

AI-based mobile fundoscopy is more than a technological marvel; it catalyses 'RevoVational' (revolutionary change driven by innovation) change that propels us toward a vision of a healthcare system characterised by accessibility, affordability and excellence. As we stand on the cusp of this new era, it is incumbent upon us to embrace this change, foster the growth of AI in healthcare and collectively ensure in future that medicine not only reaches everyone but also delivers the exceptional care that every person deserves.

The system must undergo a 'RevoVational' change. It is imperative to re-establish protocols that leverage available AI solutions to revolutionise GPs, pharmacy- and nurse-based primary care practitioners.

By embracing this modality, we are stepping into a future where primary care providers become the vanguard of disease prevention and early intervention, wielding the tools necessary to address health concerns at their inception.

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ENHANCING POST-DISCHARGE Outcomes with AI-Enabled Care Coordination Platforms

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EXECUTIVE SUMMARY

Background: In South Africa, 90-day readmission rates hover around 15-20%, adversely impacting patient health and increasing healthcare costs. This highlights the need for innovative solutions like AI-enabled care coordination (CC) platforms to improve post-discharge care quality and reduce expenses for both patients and medical schemes.

Objective: To illustrate how leveraging an AI-enabled CC platform can automate post-discharge care, reduce readmission rates, optimise healthcare costs and enhance patient satisfaction.

Methodology: The approach involves using an AI-platform with integrated care journeys for all medical conditions and procedures. The platform, capable of processing both structured and unstructured patient information, creates personalised follow-up schedules based on patient risk profiles, enhancing care through digital and human touchpoints. Discharge summaries of members' hospitalisation claims along with care managers (CMs) are required to execute the platform.

Results: Utilisation of the AI platform led to:

- For medical schemes, a 30-45% reduction in 90-day readmission rates and an average 8-12% reduction in healthcare costs.
- Improved health outcomes and patient satisfaction.
- Better clinical outcomes for hospitals and increased patient loyalty.

Conclusion: The AI-enabled CC platform significantly contributes to optimising post-discharge health outcomes and reducing healthcare expenditures, showcasing its potential as an affordable, sustainable, and scalable solution for medical schemes and/or managed care organisations.

INTRODUCTION

A hospital readmission is defined as the return of a patient to an acute care hospital, within a specific time frame, after being discharged (Mayo Clinic, 2020). Readmissions are seen as both costly and preventable (Basu, et al, 2015). They use up resources that could be used by other patients. Readmissions are of two types: Planned readmissions (PRs), which are decided during the patient's last discharge, and unplanned readmissions (URs), which happen without warning and are usually related to initial hospitalisation (Kossovsky, et al, 1999; Archer, 2012). URs are generally considered to be the primary indicator of quality of care provided by healthcare systems (Sarasin, et al, 1999). A significant type of readmission involves cases where a patient is readmitted for a reason clinically related to the previous hospitalisation within a specified time interval (Zhang, et al, 2019). Readmission rates are a critical metric for assessing the quality of hospital care, identifying areas of improvement, reducing risk of adverse outcomes and addressing financial repercussions associated with poor hospital performance (Shaw, et al, 2020; Lee, et al, 2017; Jencks, et al, 2011). Various factors contribute to the risk of readmissions, including inadequate initial treatment, hospital length of stay (LOS), poor discharge planning and lack of post-discharge CC (Pugh, et al, 2021; Mohajon, 2020). Readmissions not only adversely affect patient outcomes but also impose a significant financial burden on healthcare institutions (Pugh, et al, 2021). Worldwide, URs remain a significant contributor to healthcare costs. While readmission rates vary from 10% to 25%, based on different evaluation criteria, their effect on healthcare expenses is universally recognised (Garcia-Perez, et al, 2011). In South Africa, readmissions can place an added strain on an already overburdened healthcare system (Amoah & Mwanri, 2016). Early intervention and consistent follow-up with discharged patients are essential for identifying deviations from expected recovery paths and preventing URs. This paper introduces an innovative approach that employs an AI-enabled platform to streamline post-discharge care management, aiming to reduce the incidence of URs and alleviate the financial strain on the healthcare system.

BACKGROUND

Healthcare institutions have adopted various strategies to mitigate URs and reduce the financial impact on health systems. These strategies include implementing evidence-based practice for treatment, care transition programmes, enhanced discharge planning, medication management and infection control programmes. Although these interventions are designed to improve the quality of in-hospital care and reduce the likelihood of readmission, they often do not extend to monitoring patients post discharge.

A prevalent misconception within the health community is that a patient's episode of care begins with diagnosis/admission and ends upon discharge. However, the reality is that the episode of care extends beyond discharge, ending only when the patient is fully recovered from the condition that necessitated hospitalisation. Post discharge, patients are expected to adhere to a care pathway that guides their recovery journey. Any deviations from these expected care pathways can result in URs, adversely affecting health outcomes and escalating healthcare costs. Therefore, proactive monitoring of patients post discharge to identify any deviations from their care pathways is essential for reducing the likelihood of URs.

Traditionally, hospitals have played a crucial role in admitting patients, diagnosing their conditions, providing appropriate treatments and ensuring stability before discharge. This continuum of care, while comprehensive up to the point of discharge, often concludes at this juncture, leaving a gap in the ongoing monitoring of the patient's condition post discharge. It is at this juncture that the responsibility should transition to medical schemes, extending the continuum care beyond the hospital's doors. It is imperative for schemes to monitor patients post discharge. This is because if a patient is readmitted, the scheme will have to cover the costs of the additional care. Thus, the care transition post discharge is not merely a matter of continuity, it represents a strategic move to ensure a patient's full recovery and to avoid the financial burdens associated with readmissions.

PROPOSED SOLUTION

An effective solution to the challenges highlighted in the background section involves the adoption of highly automated and smartly driven CC platforms by medical schemes. Given the high volume of members discharged daily, a manual approach to post-discharge care management (PDCM) is impractical. Therefore, a system that automates the CC process, removing the manual workload from CMs, is essential. The envisioned CC platform boasts several key features designed to streamline and enhance the follow-up process with larger populations:

(a) Integrated care journeys for every medical condition and procedure across all specialities, ensuring comprehensive care coverage.

(b) Advanced algorithms capable of proactively identifying the post-discharge risk and symptoms of each member, enabling early intervention.

(c) The assignment of members to a specific CM for personalised care, fostering a more tailored approach to post-discharge support.

(d) Guidance on who to intervene, when to intervene and what intervention to make.

(e) Automated scheduling of digital and human touchpoints.

(f) Multi-channel intervention capabilities, including telephonic, text messages, WhatsApp and email communications to accommodate diverse member preferences and enhance self-care.

(g) The continuous refinement of clinical protocols based on member feedback and interventions.

(h) An integrated physician appointment booking system, simplifying the process of arranging follow-up care.

(i) Mechanisms for identifying and referring members to ancillary medical services as needed.

(j) Provision of educational material support for patients to improve medical understanding, thereby promoting adherence to a treatment plan.

METHODOLOGY

The success of the PDCM programme hinges on three foundational elements:

(a) Data requirements: Access to a comprehensive discharge summary or the claims information related to the member's hospital discharges.

(b) Technology: At the core of our approach is the implementation of an AI-enabled CC platform. This web-based platform, fully co-developed by the authors, leverages both structured and unstructured member data to automate the CC process. It has been deployed by medical schemes and hospitals across India, the United States, Singapore and the Middle East. To facilitate broad and affordable access, the platform is offered on a licensing model at ZAR3-4 per active beneficiary per month. No other direct costs for system set-up and maintenance are charged, ensuring economical solutions for partners.

To date, the platform has facilitated over five million interactions. Utilising AI algorithms, it matches current members' risk profiles with similar risk profiles in a vast database, predicting deviations from care pathways. Whenever there is a deviation, the platform promptly schedules an interaction (touchpoint) with the CM. This adaptive algorithm continually refines its risk assessment based on additional post-discharge recovery data collected, ensuring tailored post-discharge care.

To ensure scalability and adherence to international data protection standards, the platform is ISO 27001 and HIPAA compliant, ensuring data security and privacy. Additionally, to meet regional data security requirements, the data are hosted on AWS servers located within the respective country of operation.

(c) Human resources: The AI platform requires only two CMs for every thousand discharges, compared to six CMs required for manual operations, achieving a 66% reduction in the human resources needed. These CMs utilise assigned credentials to access the platform, focusing on cases flagged by the system based on members' risk profiles. Their primary role involves proactive engagement with assigned members to monitor for any complications, ensuring timely intervention and personalised care.

Integration and practical application

Successful integration of the CC platform within the existing healthcare data infrastructure is critical. This includes:

(a) Ensuring seamless data-sharing between healthcare providers to maintain a continuous flow of member information.

(b) Upholding strict data privacy and security standards to protect member information.

(c) Providing comprehensive training for CMs to effectively utilise the platform.

The platform supports API-, FHIR- and HL7-based integrations for seamless data exchange across different health systems. In scenarios where direct integration is not feasible, the platform accommodates manual inputs through Excel or PDF files containing discharge summary details.

Discharge analysis and risk profiling

Upon receipt of discharge/claims data, the CC platform's advanced AI algorithms analyse each member's information, creating a unique risk profile (URP) for every member, based on factors like age, gender, diagnosis, treatment undergone and LOS. Members are stratified into high-risk (HR) and low-risk (LR) cohorts based on their URPs, allowing for targeted and efficient post-discharge care interventions.

Synthesising individual care plans

With URPs as a guide, the platform customises a care plan for each member. These plans list the potential post-discharge symptoms that a member could experience on their journey to recovery.

Assignment of touchpoints

An evidence-based calendar of touchpoints is automatically generated for each member according to their risk profile. The HR members receive more frequent touchpoints compared to LR members to closely monitor their recovery.

Operationalising the care plan

The execution of the care plan involves a two-pronged strategy. Firstly, the platform schedules a dynamic calendar of touchpoints based on the URP. Secondly, it populates relevant clinical content for CMs to have meaningful interactions with members. This strategy focuses on symptom checks, medication adherence, physician visit compliance, reminders about follow-up visits and the arrangement of required ancillary services. These structured and timely interactions aim to reduce URs by identifying if a member is deviating from their care plan and experiencing complications. All members who experience complications are redirected to the physician for a corrective course of treatment, thereby preventing readmission or reducing the severity of readmission.

RESULTS

A nationwide PDCM programme, in collaboration with a leading medical scheme in South Africa, involving approximately 5000 intervenable claims per month, is currently in its implementation phase. The comprehensive review of the programme's outcomes is scheduled for February 2025. In the interim, to evaluate the impact of the AI-enabled CC platform, we draw upon the outcomes from a similar programme aimed at reducing URs conducted with a private medical scheme in India.

We compared 'baseline' metrics – data from the year before the PDCM programme's initiation, without AI intervention – to 'post-period' metrics collected in the year after the AI-platform was deployed. This scheme had 10 000 intervenable claims per month for the financial year 2022-2023. The baseline analysis of the previous financial year revealed a 12.0% unplanned readmission rate (URR), accounting for 14 400 readmissions a year at an average cost of readmission (ACR) of ZAR19 843.

Reduction in readmission rates and ACR

A year after PDCM programme's implementation, results indicated a significant reduction in readmissions and ACR. The 90-day URR dropped by 44% from 14 400 to 8 064 instances of readmission a year. The ACR plunged by 11% to ZAR17 660. The total cost of 90-day URs dropped from ZAR286 million to ZAR142 million in a year. These improvements yielded savings of ZAR143.3 million.

Figure 1. The reduction in 90-day unplanned readmissions, comparing baseline date with post-programme outcomes, highlighting the efficacy of the AI-platform in mitigating readmissions.

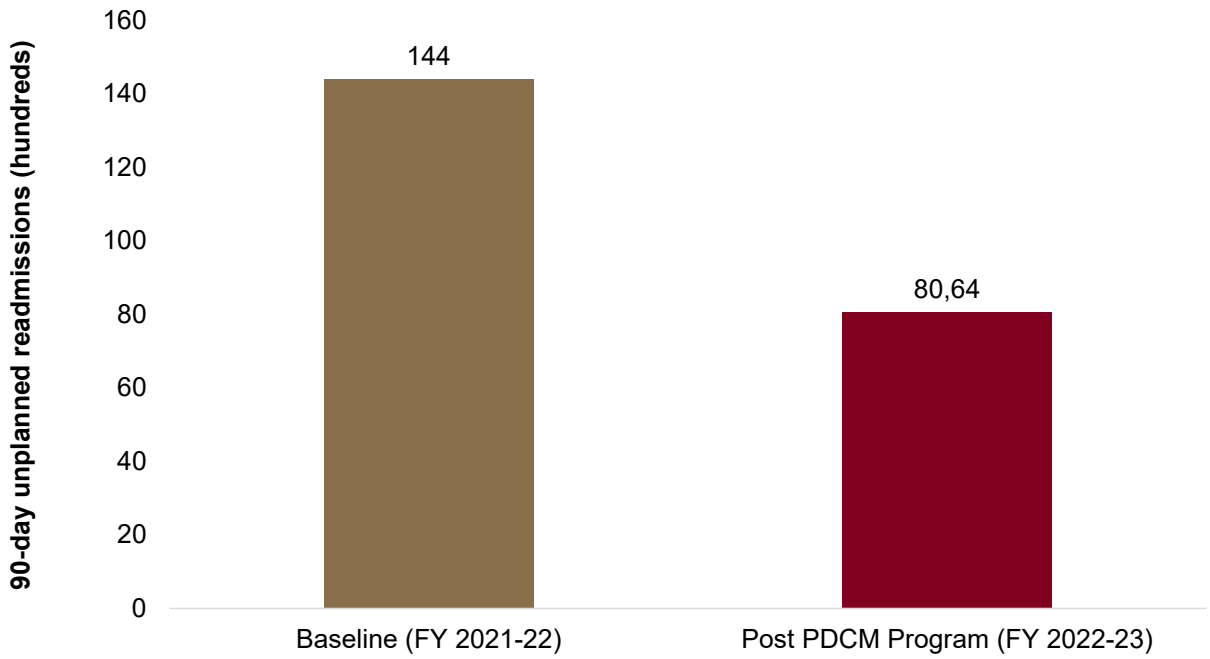
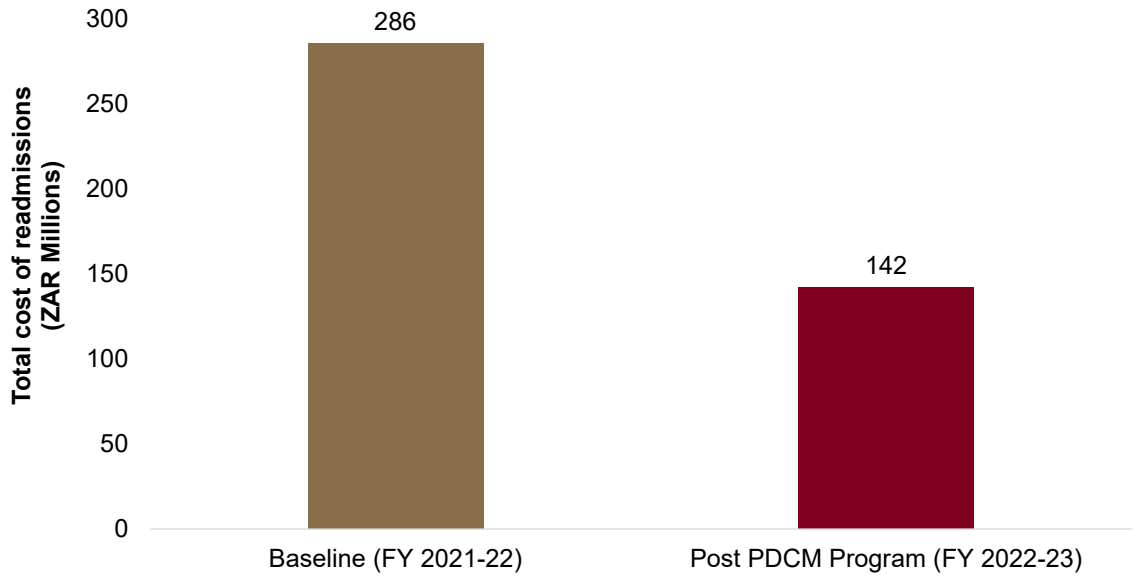


Figure 2. The comparison of total readmission costs before and after the PDCM programme, showing the cost-savings achieved through AI optimisation



INSIGHTS INTO SPECIALTIES AND DEMOGRAPHICS

The analysis highlighted that specialities such as cardiology, endocrinology, neurology and pulmonology exhibited the highest readmission rates. Additionally, data indicated that males and the elderly were more prone to readmissions, underscoring the importance of focused attention in these areas.

Figure 3. The reduction in 90-day unplanned readmissions across the top four specialities, comparing the baseline and post-programme periods.

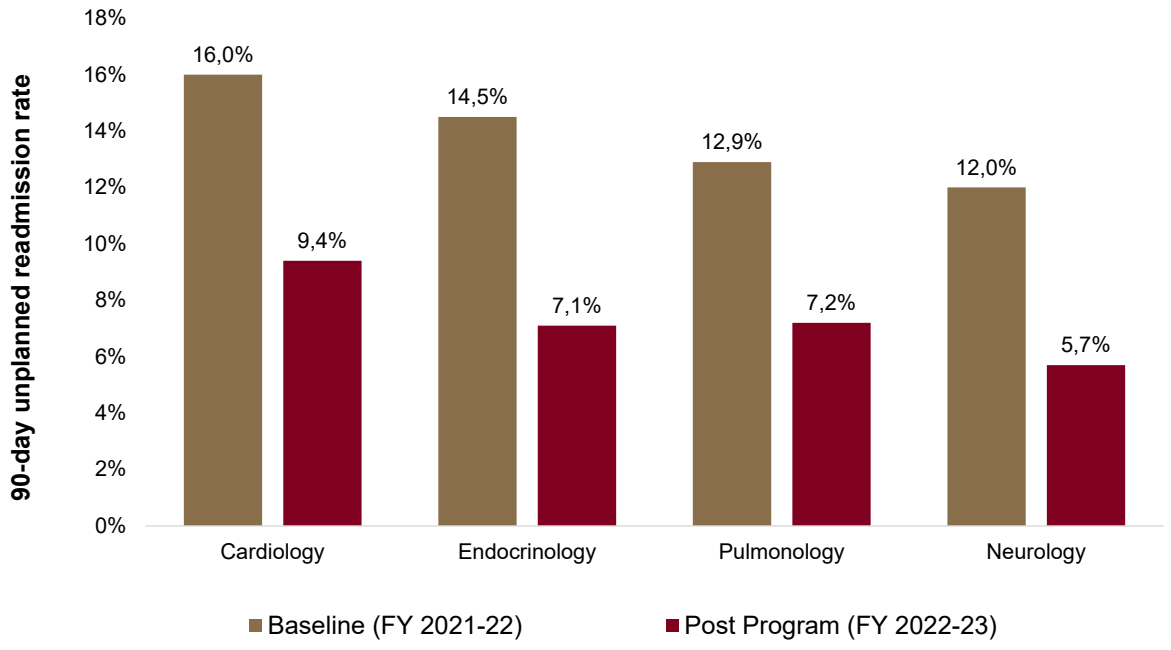
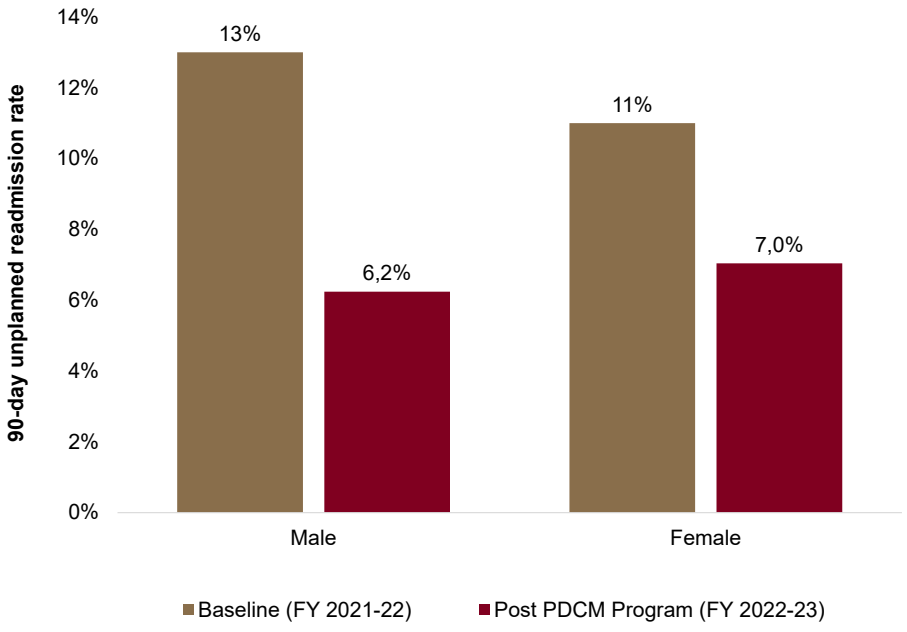


Table 1. Comprehensive overview of baseline and post-programme 90-day URRs and volumes by speciality

Speciality	Baseline URR	Baseline URs	Post-programme URR	Post-programme URs
Infectious Diseases	10.1%	806	5.2%	415
Haematology & Immunology	10.0%	360	6.3%	227
Endocrinology	14.5%	695	7.1%	340
Neurology	12.0%	1008	5.7%	479
Cardiology	16.0%	3306	9.4%	1947
Pulmonology	12.9%	2331	7.2%	1301
Gastroenterology	11.0%	2117	5.8%	1116
Dermatology	7.0%	210	5.5%	165
Rheumatology & Orthopaedics	7.5%	843	4.3%	484
Urology & Nephrology	12.0%	1462	6.7%	816
Obstetrics/Gynaecology	11.1%	1261	6.8%	774
Total	**12%**	**14400**	**6.7%**	**8064**

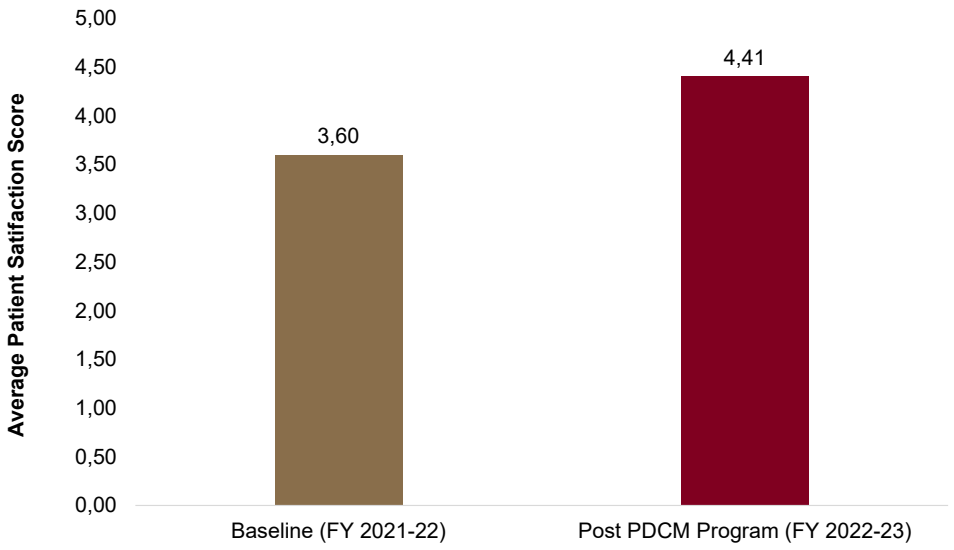
Figure 4. Gender-wise comparison of 90-day URRs, illustrating the effect of the AI platform on reducing readmissions across male and female members.



ENHANCED MEMBER AND HOSPITAL OUTCOMES:

Beyond financial metrics, the programme has led to marked improvements in member health outcomes and satisfaction levels by reducing URs. Hospitals that participated in the programme reported improved clinical outcomes and patient satisfaction. The baseline analysis showed patient satisfaction scores at 3.6 on a scale of 5. Post the PDCM programme, these scores rose by 22% to 4.41, reflecting the programme's positive impact on patient experiences. This increase was measured through a single-item survey where members were asked: "How satisfied are you with the services provided by the hospital?" These findings demonstrate the AI-enabled CC platform's role in enhancing member care and it's potential as a scalable and sustainable solution across healthcare settings.

Figure 5. Satisfaction scores before and after the programme's implementation, underscoring enhanced patient experiences.



CONCLUSION

This study demonstrated the significant impact of AI-enabled CC platforms in optimising post-discharge outcomes and reducing healthcare costs. By automating follow-ups and tailoring care plans based on URPs, the platform has proven to be a critical tool in managing post-discharge care. The reduction in readmission rates and healthcare expenditure, alongside improved patient satisfaction and clinical outcomes, highlights the platform's value as a scalable solution for medical schemes. Future efforts should focus on expanding the integration of such platforms within existing healthcare infrastructure to further enhance patient care continuity and cost efficiency.

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INNOVATING HEALTHCARE: The Power of Value-Based Care Models

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EXECUTIVE SUMMARY

South Africa (SA) is faced with escalating costs of care, the increasing prevalence of chronic diseases and an ageing population in a fragmented and volume-driven private sector, while the quality of care is not optimised. To achieve a sustainable healthcare system, there must be a fundamental shift towards a value-driven, patient-centred delivery model, in which healthcare providers are reimbursed based on the value of care delivered to the patient.

As value-based purchasing has not been widely adopted in SA, this study performed an in-depth qualitative analysis of three value-based care (VBC) models that have been implemented. The analysis focused on the principles of each model, the extent to which each model had incorporated the six pillars of the Value Agenda by Porter & Lee (2013), and whether the intended VBC outcomes had been achieved. The analysis was further elucidated by semi-structured interviews aimed at identifying the barriers to and enablers of successful VBC delivery.

Findings showed that the three models had implemented elements of the Value Agenda to varying degrees. That VBC can improve health outcomes and reduce costs was well demonstrated.

The study also found that in order to address the current barriers to the implementation of VBC, there needs to be collaboration between funders and healthcare providers, as well as a review of current legislative frameworks and benefit design limitations that may hinder the progressive implementation of VBC in SA.

INTRODUCTION

Significant challenges faced by healthcare sectors worldwide include the escalating costs of care, the increasing prevalence of chronic diseases and ageing populations (Walsh, et al, 2020). Three of the eight Sustainable Development Goals (SDGs) aim to improve health outcomes. This highlights the importance of health in global economic development. While other low- and middle-income countries have made significant progress in achieving health-related SDGs, SA continues to experience a challenge in achieving positive outcomes in this regard (Hlafa, et al, 2019).

The Health Market Inquiry (HMI, 2019), appointed by the SA Competition Commission to review the state of the private healthcare sector (in addition to competition dynamics), raised concern over the increasing cost of care in a severely fragmented, volume-driven and hospicentric private healthcare system.

LITERATURE REVIEW

Porter and Lee (2013) argue that healthcare must fundamentally shift towards a value-driven, patient-centred delivery model to ensure its sustainability.

In contrast to the fee-for-service model, which incentivises healthcare providers based on the volume of services delivered, VBC reimburses healthcare providers based on quality of care, improved patient outcomes and cost-containment (Modica, 2020).

The value equation in Figure 1 depicts a fundamental change in how outcomes are captured, reported and measured. It focuses specifically on identifying the appropriate measures for clinical and patient-centred outcomes.

Figure 1. The Value Equation (Porter & Lee, 2013)

Several authors have identified various frameworks that can be applied in the transition to VBC. These frameworks date back to the 1960s, with Donabedian's Triad of Structure, Process and Outcomes which was most likely the first proposed solution to ensuring healthcare delivery that can be linked to and measured against quality outcomes (Ayanian & Markel, 2016). More recent frameworks include the Triple Aim, underpinned by three overarching goals: improving patient experience and population health, and reducing healthcare costs (Berwick, et al, 2008). In an effort to acknowledge the critical role of healthcare providers in healthcare transformation, Sikka, et al (2015) proposed a modification of the Triple Aim into the Quadruple Aim through the addition of a fourth aim: improving the experience of providing care, which considers the sense of accomplishment and meaning in the contributions made by healthcare providers.

Figure 2. The Value Agenda (Porter & Lee, 2013)

Perhaps the most well-known and most referenced VBC framework is Porter and Lee's Value Agenda (2013). The Value Agenda (Figure 2) has six independent but mutually reinforcing components. It emphasises the importance of value-driven, patient-centred care and reimbursing/incentivising healthcare providers for performance/value.

The author's review of the literature shows that these frameworks have the following principles in common:

- Creating value for the patient;
- Measuring clinical outcomes through cost efficiency and improved population health; and
- Reducing costs.

In SA, value-based purchasing has not been widely adopted. Sandy, et al (2019) report a general lack of trust between healthcare providers and funders, with providers perceiving value-based initiatives as an intrusive and punitive effort by funders to micromanage them.

The Council of Medical Schemes (CMS) (2018) also stated that since fee-for-service was becoming a less attractive way of contracting in healthcare, alternative reimbursement models should form the basis of future healthcare reimbursement dispensations.

To address the dearth of peer-reviewed literature on the analysis of VBC models in the SA context, this study performed an in-depth analysis of the VBC models that have been implemented in the SA primary healthcare sector. To achieve this aim, the objectives of this study included:

- The analysis of three identified VBC models implemented in the primary healthcare context.
- The determination of the extent to which each model had incorporated the six pillars of the Value Agenda by Porter & Lee (2013).
- The determination of whether the intended value-based outcomes had been achieved.
- Gaining a better understanding of the barriers to and enablers of the delivery of VBC in SA.

METHODOLOGY

An in-depth study of three identified VBC models was conducted through a qualitative desk-top analysis of information available in the public domain, as well as anonymised reports on quality outcomes and cost.

The analysis was performed against the six pillars of the Value Agenda by Porter & Lee (2013) to determine the extent to which these models had incorporated these pillars. Findings were further elucidated by semi-structured interviews conducted solely with each entity's key representatives. ATLAS.TI 9 was used for thematic analysis of the interviews.

The population sample used consisted of VBC models implemented in collaboration with the Government Employees' Medical Scheme (GEMS). The research analysis utilised anonymised in- and out-of-hospital claims and clinical outcomes data reported between 1 January 2017 and 31 March 2020. Ethical approval for this study and explicit consent from all interviewees were obtained. The three models identified for this study are described in Figure 3 below:

Figure 3. VBC models used in the analysis

PARTICIPANTS

PPO Serve
Intergrated Clinical Consortia™

The Population Medicine Pilot in Pretoria North was established through a multidisciplinary team approach, the Value Care Team (VCT). The VCT included general practitioners (GPs), specialists, social workers, psychologists, physiotherapists, and registered nurses.

Pilot site was pre-determined based on a large population of high-risk GEMS beneficiaries (with poorly controlled chronic conditions, multiple comorbidities, and multiple hospital admissions). Approximately 5600 beneficiaries enrolled.

PPO Serve Intelligent Care System (ICS®), a comprehensive patient management system was used as a hub for electronic health records, and to support the VCT in managing patient care plans and monitoring outcomes and costs.

The VCT was reimbursed through a performance-based fee structure.

DBC
Licensed by Klinikka (Pty) Ltd

Rehabilitation programme for patients with chronic back/neck ache. Unique back and neck treatment equipment used for rehabilitation.

Multidisciplinary teams (GPs, biokinetics) followed set Klinnika Pty (Ltd) evidence-based clinical protocols aimed at improving outcomes.

Eligible patients were identified using GEMS claims and admissions data analytics, and actively enrolled in DBC Centres across SA.

Patient care was coordinated around the patient's medical condition, including treatment, education, and counselling.

Alternative-reimbursement arrangement in the form of global fees.

gems
Emerald

Efficiency Discount Option (EDO) of the traditional Emerald Option (2nd highest GEMS benefit option), with the same comprehensive benefits.

Underpinned by care coordination (in this case, comprised of the GP acting as the first point of care, ensuring that care is delivered at the right level, GP-to-specialist referrals, and the use of efficient network contracted hospitals).

Contracted network GPs (over 7 000 across SA) reimbursed based on a predetermined performance scorecard.

Specialists reimbursed on a fee-for-service basis.

Hospital network contracted on cost and quality performance.

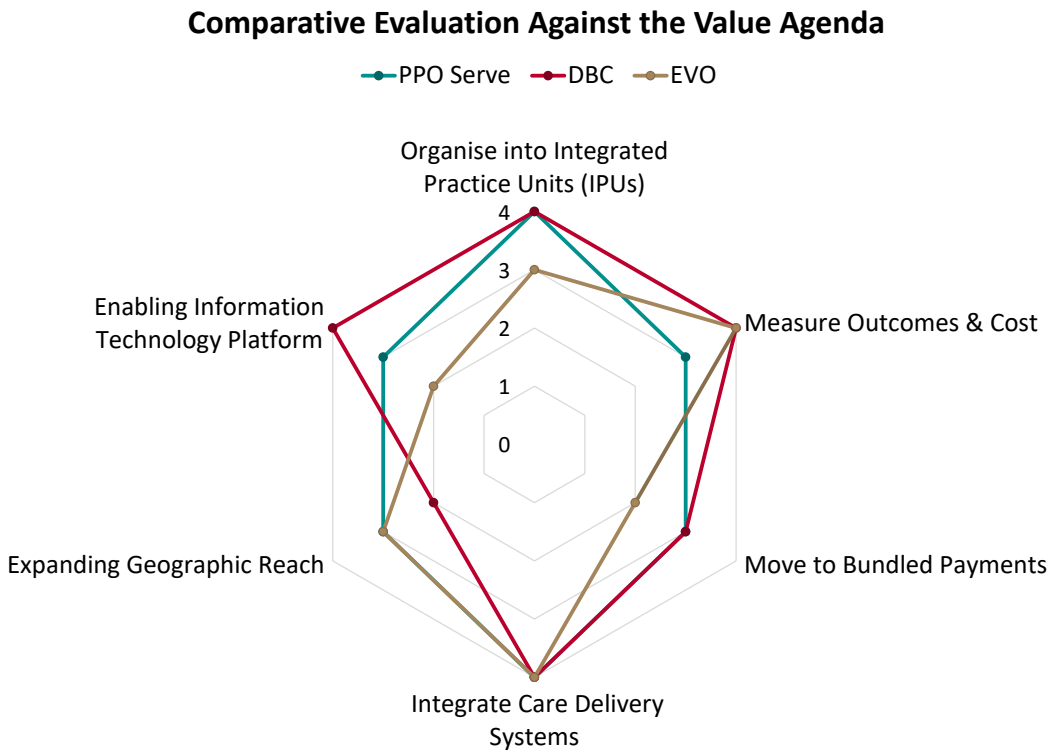
FINDINGS

Analysis against the six pillars of the Value Agenda

When compared against each other based on a rating scale that was used to determine the extent to which the six elements of the Value Agenda had been successfully implemented, all three of the models were found to have implemented elements of it to varying degrees as illustrated in the spider diagram in Figure 4.

The PPO Serve population medicine pilot, while limited to one site, successfully incorporated all elements of the Value Agenda. Throughout the pilot, a predetermined aggregate score that measured surrogate outcomes such as risk-adjusted admission rates, cost per admission and re-admission rates for chronic disease management such as HIV, cardiovascular disease and asthma showed a 30% increase in performance. While the pilot performed well on outcome measures for chronic disease management, performance fell within lower percentiles on some metrics (such as surgical admission rates) when compared to healthcare providers that were not pilot participants.

Figure 4. Spider diagram illustrating the comparative analysis of the three models against the Value Agenda



Poor (1)	Acceptable (2)	Good (3)	Exceptional (4)

The GEMS Emerald Value Option (EVO) incorporated only four of the six elements of the Value Agenda, but by incorporating care coordination into its benefit design, it demonstrated a 17.7% reduction in hospital admission rates, a 12.4% decrease in hospital costs per admission and an overall reduction in per-life-per-month expenditures (when compared to the traditional Emerald Option).

The DBC model, which implemented five of the six Value Agenda elements, resulted in a 32% reduction in spinal surgery. There was an 8.5% reduction in readmission rates for medical back and neck pain management, a 68% improvement in enrolled patients' range of movement, and a 93% reduction in reliance on pain medication. Furthermore, 93% of the enrolled beneficiaries were satisfied with the service they received, with 98% indicating that they would recommend the programme to others.

Semi-structured interviews

Four main emerging themes are discussed below further to the ATLAS.TI 9 thematic analysis of the semi-structured interviews.

Theme 1: Problems in the healthcare system that necessitated the development of VBC models

The interviews revealed that the VBC models analysed in this study were conceptualised as a solution to various problems in the healthcare sector. These included the escalating costs of care, hospicentric and fragmented care, and wasteful expenditure by healthcare providers, who benefit from fee-for-service reimbursement models. The interviewees also highlighted the importance of primary and coordinated care as the foundation of an efficient healthcare system.

Theme 2: Actions to advance VBC initiatives

In this regard, the interviewees were of the view that the consolidation of medical schemes would give way to alternative reimbursement arrangements, which would favour value and quality. Funders would need to strategically review their benefit designs and ring-fence funds for these initiatives.

Theme 3: Enablers of successful implementation of VBC models

The interviewees attributed the success of these three models to the fact that they were founded on the principles of teamwork. Furthermore, the digital revolution was thought to have propelled the success of VBC models such as the ones evaluated in this study, with participants noting that they had access to data-focused research that, in turn, translated to an understanding of clinical needs and outcomes that were data-driven. Knowledge of information systems and operational expertise was also thought to be fundamental to the implementation of such models.

Theme 4: Barriers to the implementation of VBC models

The interviewees reported that legislative frameworks that hindered elements of VBC models were the overarching barriers to their implementation. They also noted that teamwork linked to reimbursement models such as global fees was deemed unethical by the CMS and governing bodies like the Health Professions Council of SA (HPCSA), resulting in resistance to industry participation in such models.

DISCUSSION

Despite the six components of the Value Agenda having been incorporated to varying degrees, the three models analysed in this study demonstrated that the intended VBC outcomes had also only been achieved to varying degrees.

The PPO Serve population medicine pilot and DBC programme demonstrated the importance of multidisciplinary teams in the transition to VBC, with both these models objectively contributing to improved healthcare outcomes while containing the cost of care. As Jesmin, et al (2021) have reported, while team-based care is expected to perform better than care provided in silos, the results are often mixed at best, as is the case with the PPO Serve population medicine pilot.

With a focus on primary healthcare and coordinated care, the EVO model successfully demonstrated the importance of making primary care the foundation that underpins an effective and efficient healthcare system, as Smolowitz, et al (2015) reported. It also demonstrated the importance of providing care at the right level. With the EVO model having incorporated only four of the six elements of the Value Agenda well, enabling technology platforms for centralised and standardised electronic medical records/repositories would further support the clinical aspect of care coordination and referral between clinicians.

The semi-structured interviews revealed that all three models were conceptualised and established as solutions to the current fragmented private healthcare industry, which is not outcomes driven.

The importance of primary and coordinated care as the foundation of an efficient healthcare system also emerged as a common theme. As Porter (2009) states, when there is poor access to primary and preventive care, significant inefficiencies result, and high-value care is challenging to achieve. This is further supported by Smolowitz, et al's (2015) argument that early utilisation of primary healthcare services is associated with efficient healthcare expenditure, improved patient health outcomes and reduced health disparities.

In line with Jesmin et al's (2015) assertion that team-based care has been used as an integral component of primary healthcare to curb escalating costs and improve deteriorating quality, one of the interviewees indicated that their programme's primary focus was to demonstrate the importance of clinicians working together as teams, leveraging their knowledge and skills to fix the 'broken' healthcare system.

It is clear, however, that further enhancement of these VBC models will only be possible if funders and healthcare providers work together to achieve success.

In this study, the over-arching barriers to implementing VBC models were reported to be CMS and HPCSA legislative frameworks that hindered elements of these models. This is, however, contrary to what Barr, et al (2019) reported, citing medical scheme benefit design and lack of collaboration between funders and healthcare providers as the most significant barriers to the implementation of VBC in SA. However, it is not clear whether the CMS was an actual or perceived barrier, as the CMS itself has previously expressed the view that alternative reimbursement models should form the basis of future healthcare dispensations (CMS, 2018). Regardless of the findings, what became clear was that collaboration between funders and healthcare providers and proactive engagements with legislative bodies like the CMS and HPCSA is imperative to finding solutions to a sustainable private healthcare system in SA.

CONCLUSION

The models analysed in this study demonstrated that VBC can improve health outcomes while simultaneously reducing healthcare costs.

Similar to what Porter and Lee (2013) reported, the components of the Value Agenda exist to varying degrees in the models analysed in this study. Continuous improvement is, therefore, critical to achieving full implementation. Data-focused research and technical expertise also play a critical role in enabling and implementing VBC.

Collaboration between funders and healthcare providers is essential to address current barriers to VBC implementation. Furthermore, a review of current legislative frameworks and benefit design limitations that may hinder its progressive implementation is essential.

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COMBATING MISUSE AND ABUSE IN HEALTHCARE:

Strategic Insights from a Clinical Audit

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EXECUTIVE SUMMARY

Misuse and abuse of healthcare systems can take various forms and have significant consequences for individuals and society. It aggravates an already cash-strapped service, making it more unaffordable. Misuse can delay care with consequent medical complications that have both economic and financial costs. Abuse syphons off funds without adding to the health status of individuals or the country. Mitigating misuse and abuse has a triple positive effect - it improves the patient experience, improves population health and reduces the per capita cost of healthcare.

Addressing the misuse and abuse of healthcare systems requires a combination of regulatory measures, greater clinical awareness among scheme members, sometimes patient or service supplier education and clinal audit to assess and evaluate the value, both financially and clinically, of supplier interventions.

Stricter oversight, improved data analyses and enhanced collaboration between healthcare stakeholders are essential to combat misuse and abuse and thus ensure the integrity and sustainability of a healthcare system.

This clinical audit aims to differentiate between misuse and abuse with examples, since the remedial strategic interventions required are different.

INTRODUCTION

This clinical audit explores the nature of medical misuse and abuse. The triple aim of improving a healthcare system, which would include minimising both misuse and abuse, is to improve the patient experience, improve population health and reduce the per capita cost of healthcare (Berwick, et al, 2008).

Misuse and abuse of healthcare systems is considered to be internationally widespread and poses a significant threat to public health, patient well-being and healthcare financing. There have been various estimates of the extent of medical fraud, unintentional misuse and intentional abuse. It is thought to cost healthcare systems hundreds of billions of dollars every year. (Speer, et al, 2020). Wasteful healthcare spending can be classified into six categories: clinical inefficiencies, missed prevention opportunities, overuse, administrative waste, excessive prices, and fraud and abuse. Estimations vary because the parameters are not clearly defined and often go unrecognised. Both misuse and abuse cause waste: hence the need to try to develop better definitions of both and how they occur. Misuse, here, is the unintentional use of unwarranted consultations, medicines, medical procedures and referrals. Abuse, on the other hand, is the informed generation of medical goods and services for personal gain that does not obviously advance patient well-being. There is some recognition that reforms of the healthcare system are needed to bring about a fundamental redesign thereof and also improve its quality and safety (Institute of Medicine (US) Committee on Quality of Healthcare in America, 2001). One of the recommended components of this redesign is to better align the incentives inherent in payment and accountability with improvements in quality of care.

Developing a reporting culture was initially thought to be a tool to learn from close calls and hazardous conditions in healthcare (Joint Commission, 2019). Using claims data for clinical audit promotes safer care and can also be used to identify misuse and abuse in any system. The clinical audit process integrates and evaluates the best research evidence, clinical expertise and the help-seeking behaviour of the patient.

Much of the published literature seems to suggest that misuse and abuse is due to supplier error and public and suppliers' perspectives on these errors (Blendon & DesRoches, 2002; Spath, 2011). Misuse can be an error. However, abuse is intentional misuse for personal gain and is not an error.

METHODOLOGY

Twelve months' worth of claims data from a medical scheme with more than 300 000 beneficiaries was electronically downloaded from the administrator. An internally developed customised information tool, 'Explorer', was used to deliver an epidemiological view of the data for analysis. Claims data were evaluated quarterly.

RESULTS AND DISCUSSION

An overall view of the members' and registered beneficiaries' claims for a representative three-month period of the year is presented in Table I.

Table I. Members, beneficiaries and expenditure for the fourth quarter.

Members Registered	118,812
People Registered	328,346
People Claiming	257,339
No of Payments	5,186,632
Date From	1 Oct 19
Date To	31 Dec 19
Claimed Amount	R2,081,476,522.10
Benefit Amount	R1,746,151,728.74
Medicine Benefit	R290,374,548.29
Hospital Benefit	R1,066,860,488.59

The number of claimants for this quarter comprises 78% of the beneficiaries. This large claiming ratio raises the suspicion of a significant element of overutilisation of benefits. This could be either legitimate or fraudulent - the former would be regarded as misuse or unintentional errors, while the latter, abuse or intentional errors. Assuming all claims are legitimate, motivated by a need for healthcare services, then the deduction is that either the aetiology of the presenting symptoms has not been fully investigated and therefore the treatment plans lack an essential remedial intervention - an example of unintentional error due to incomplete investigation. The alternative is that the diagnosis is correct, but the treatment plans are inadequate. Once again, an unintentional error and an example of misuse. However, if the cases were fully investigated and knowingly not appropriately remediated, this would constitute abuse by the patient, the supplier of the service or by unsuitable benefit design. Either way, all possibilities need to be investigated and addressed, either with health education and behaviour change or changes to the benefit system.

Adverse contributing environmental aetiological factors may not always be fully investigated. In a fee-for-service (FFS) system, clinical services tend to follow rewards. Generally, in FFS, treatments for diagnoses and symptoms take precedence over aetiology. Repeated contacts with the same or a similar type of service supplier are often the first indication of misuse or abuse.

No medical benefit system can survive if the wrong remedies are prescribed. What might not be quite so obvious is that if the contributing environmental aetiological factors are not identified, investigated and resolved or if known incomplete or inadequate remedies are repeatedly prescribed, it has the same effect on the healthcare system. An analogy would be like trying to fill a bucket with water when it has a hole. Someone needs to examine the bucket!

An aetiological category that is often neglected comprises contributing psycho-socio-economic factors, chronic conditions and recurring infections.

In Table I out-of-pocket payments account for 20% of the expenditure. Co-payments might be 'tipping' - an opportunity for the supplier of the service to gain financially. This can encourage some suppliers of services to opt for more economically rewarding services for their own rather than the patient's benefit. The established 20% on co-payments in this fund may, in fact, not be saving money or protecting the members. It may not only be encouraging unnecessary hospital admissions; it could also be creating hardship for cash-strapped members and may even be discouraging compliance with a chronic patient adherence to remedial plans. It is also not really a long-term solution for the scheme because the short-term benefits of avoiding payment for a primary care condition, if that is the shortcoming, can result in ongoing longer-term paying for medical complications that occur because a primary health symptom is ignored or poorly treated.

Supplier networks were once considered as an adjunct or alternative to co-payments. The results have been disappointing. Improving patient primary care with targeted research and the ongoing monitoring of help-seeking behaviour is preferable. Using targeted and appropriate interventions, by monitoring help-seeking behaviour, has proved to be a better monitor of misuse and abuse and a more appropriate long-term solution.

The 51% of hospital budget expenditure in Table I endorses the need for better primary healthcare services. The reasons for hospital admissions therefore need reviewing. If a patient is admitted for primary conditions, the benefit structure is most certainly likely, if not entirely, the reason. If they are admitted for medical complications of initially diagnosed conditions, then once again the benefit structures need reviewing. If this is not done, it may well be considered abuse. A decision needs to be made as to whether alternative earlier intervention benefits need to be considered and implemented. Health screening, the early diagnosis of conditions and community-based treatments might suffice and therefore mitigate against preventable hospital admissions.

Table II shows the type and financial costs of treating the range of conditions during this quarter. Using the anatomic therapeutic coding system of the medicines prescribed for patients provided a high-level presumptive diagnosis.

Table II. Diagnoses and costs and numbers of patients.

System1	Total Benefit	%	Qtr fc People
CNS	R1,963,529,628	25%	31,032
Antiinfective	R1,129,361,477	14%	46,846
CVS	R1,076,045,469	14%	26,551
Alimentary	R1,038,895,150	13%	34,523
Resp	R875,165,482	11%	45,909
MSS	R686,024,866	9%	24,013
GUS	R219,702,490	3%	10,875
Sensory	R201,414,224	3%	5,528
Blood	R166,765,241	2%	2,880
Derma	R162,014,570	2%	10,199
Dental	R147,702,265	2%	5,760
Immune	R100,736,714	1%	1,261
Hormonal	R84,726,949	1%	3,862
Other	R50,565,633	1%	6,498
Antiparasitic	R26,223,672	0%	1,371
Various	R593,808	0%	216

By far the greatest number of conditions are central nervous system (CNS) conditions. Anxiety, stress, insomnia, depression, post-traumatic stress, bullying, frustration and substance abuse were most prevalent. There were fewer than a dozen diagnoses of schizophrenia and bipolar conditions. In addition to the presenting CNS symptoms, many of these patients also presented with complications that developed during the year (Table lll).

Table lll. A list of comorbidities among patients with CNS conditions.

System1	System2	System3	Total Benefit	
CNS	Alimentary	CVS	R118,125,706	6%
CNS	CVS	Alimentary	R102,636,422	5%
CNS	Blood	Alimentary	R73,269,150	4%
CNS			R73,202,566	4%
CNS	CVS	Blood	R71,185,729	4%
CNS	Blood	CVS	R66,225,725	3%
CNS	MSS	Alimentary	R56,552,625	3%
CNS	Antiinfective	Alimentary	R54,137,848	3%
CNS	Alimentary	Resp	R53,007,688	3%
CNS	Alimentary	Antiinfective	R51,110,093	3%
CNS	Alimentary	MSS	R49,476,454	3%
CNS	MSS	CVS	R46,462,974	2%
CNS	Alimentary	Blood	R45,037,138	2%
CNS	Resp	Alimentary	R44,183,885	2%
CNS	Resp	Antiinfective	R42,344,529	2%
CNS	CVS	MSS	R41,697,162	2%
CNS	Antiinfective	Resp	R40,616,547	2%
CNS	CVS	Resp	R39,982,274	2%
CNS	MSS	Resp	R38,764,100	2%
CNS	Resp	MSS	R38,250,782	2%

The order of the cost of treating these conditions/comorbidities is given in the sequence from left to right in Table lll. CNS, the first column is the most expensive then system 2 followed by system 3. The significance of Table lll is that it illustrates the importance of adequately treating the presenting and underlying problems as they arise, because not fully resolving the presenting problems leads to further complications and treatment interventions. Pharmaceutical interventions alone do not suffice. Psycho-socio-economic diagnoses complete the investigations and are an integral part of any remedial interventions. A team approach, with members having a diverse range of skills, is the best option for remedial interventions.

Encounter tracking showed that the initial services were delivered by a pharmacist. This patient appears to have been seeking a diagnosis, as is evident from the number of consultations and investigations, so abuse on the part of the patient seems unlikely. The presenting symptoms appear to have been related to a gastrointestinal symptom, evidenced by 2019 Qtr 1 Sys1 in the bottom left-hand corner - possibly reflux or heartburn. However, the CNS condition was only diagnosed at a much later stage. The person profile on the right-hand side of Figure 1 shows 176 medicines from seven different pharmacies, suggesting that over-the-counter attempts to remedy the problem were unsuccessful, as were the first consultations with general practitioners. One hundred and six billable items from three different general practitioners and 18 services from three different physicians did not provide the diagnosis in the beginning. It should be evident that all the initial suppliers of service had not considered or were ignorant of the psychosocial issues that the clinical psychologist presumably eventually diagnosed and referred to a psychiatrist. Finally, the patient was admitted to hospital for a duodenal ulcer, something often associated with inadequately treated anxiety and stress. This resulted in a surgical intervention.

Figure 1. An example of presumed misuse

Person Details

Person	7587 [redacted]
Birthdate	11/07/1964 - 60
Sex	M
Area	Kwazulu Natal

Scheme	Start date	End date
PL640	3/12/1990	

Yr	Qtr	Sys1	Sys2	Sys3	Benefit
2019	4	CNS	Alimentary	CVS	47,896
2019	3	CNS	Alimentary	Blood	66,150
2019	2	CNS	Alimentary	Blood	59,201
2019	1	Alimentary	Blood	CNS	12,678

Person Profile

Description	Abbrev	Count
Pharmacist (60)	PH	176 / 7
General Practitioner (14)	GP	106 / 3
Clinical Pathologist (52) -Not in use see PATH	PA	101 / 2
Private Hospital (58)	HP	20 / 2
Physician (18)	SP	18 / 3
Radiologist (38)	DR	15 / 1
Medical Technology (37)	MT	13 / 1
Clinical Psychologist (86)	PYC	9 / 1
Psychiatrist (22)	PYI	7 / 1
Surgeon (42)	SG	5 / 1
Neurologist (20)	NG	5 / 1
Social Worker (89)	SW	5 / 0
Group Practices (50)	GP	4 / 1
Technician (75x)	CT	4 / 1
Dieticians (84)	DI	3 / 1

Patients or members who abuse the system are more likely to focus on one service and use it until either their benefits are depleted or the relationship is terminated by the service supplier. Limiting benefits also seems not to be an optimal solution, because the member continues to unnecessarily use the benefit until it is exhausted.

An example of abuse can be identified when there is overutilisation. This often manifests when a variety of unrelated conditions are diagnosed in the same member. This usually occurs when a member 'sells' their membership number to a willing buyer at an acceptable price.

Figure 2 below illustrates another example of abuse. Substance abuse related to prescription medicines needs to be investigated. Monitoring would surely have identified this abuse long before the dispensing of 171 medicines.

Figure 2. An example of possible member abuse.

Person Details

Person	7587 [redacted]
Birthdate	11/07/1964 - 60
Sex	M
Area	Kwazulu Natal

Scheme	Start date	End date
PL640	3/12/1990	

Yr	Qtr	Sys1	Sys2	Sys3	Benefit
2019	4	CNS	Alimentary	CVS	47,896
2019	3	CNS	Alimentary	Blood	66,150
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Neurologist (20)	NG	5 / 1
Social Worker (89)	SW	5 / 0
Group Practices (50)	GP	4 / 1
Technician (75x)	CT	4 / 1
Dieticians (84)	DI	3 / 1

Abuse is characterised by many repeated visits to the same or a similar category of supplier. This is commonly known as pharmacy- and/or doctor-hopping. Hopping occurs when the member abuses the system with many visits to the same or a similar service supplier for a range of privileges. This may be for legitimate services or can even include 'kickbacks' in the form of goods or cash.

Pattern recognition with AI is the most efficient method used to recognise underservicing and inadequate care. This is another form of misuse. Although reported here as 'Suppliers not-knowing', this may be the result of a fractured system or discontinuity of care in a FFS environment. Co-ordinating care requires systems and skills often beyond the scope of a single category of supplier group. Incomplete or uncoordinated care could be regarded as a job 'half done'. There are consequences for both the patient and the funder. It leads to inadequate care, relapses in the condition and additional expenses for the funder. In the patient, inadequately treated presenting symptoms often progress to more serious complications that require more expensive secondary care. In Figure 3 below the patients all have asthma. Despite doctor consultations, the condition is not being optimally assessed or managed with timely flow volume or peak flow measures. All the peak expiratory flows record a 0 below, showing that they are not being measured. Thus, there is no guarantee that the treatment regimens are optimal or adequate.

Figure 3. Supplier Ignorance.

758743	4 May 79 - 45	F	Kwazulu Natal	21 GP Consultations, 0 Specialist Consultation, 0 Peak Expiratory Flow, 0 Flow Volume Test, 21 GP Consultations, 0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 1 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Mod Lipogram
758869	3 Jan 70 - 54	M	Gauteng	7 GP Consultations, 0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
758887	21 Jun 51 - 73	F	Gauteng	2 GP Consultations, 3 Specialist Consultation, 3 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
758899	10 Mar 63 - 61	M	Western Cape	0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
758923	3 Aug 42 - 82	F	North West	10 GP Consultations, 3 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759013	20 Jan 66 - 58	M	Free State	0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759031	10 Dec 66 - 58	M	Western Cape	2 GP Consultations, 0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759088	16 Jan 62 - 62	M	Kwazulu Natal	0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759130	12 Jul 65 - 59	M	Gauteng	7 GP Consultations, 0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759142	12 Mar 66 - 58	M	Eastern Cape	11 GP Consultations, 0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759301	20 Oct 73 - 51	F	Western Cape	0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759313	26 Jun 71 - 53	M	Western Cape	2 GP Consultations, 0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759334	28 Feb 64 - 60	F	Kwazulu Natal	15 GP Consultations, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759430	30 Aug 76 - 48	F	Kwazulu Natal	12 GP Consultations, 0 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759451	8 Apr 61 - 63	F	Gauteng	8 GP Consultations, 0 Specialist Consultation, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Mod Lipogram, 0 LDL
759475	6 Mar 74 - 50	M	Free State	2 GP Consultations, 0 Specialist Consultation, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL
759487	26 Feb 44 - 80	F	Gauteng	2 GP Consultations, 3 Specialist Consultation, 0 Opthalmologist, 0 Podiatrist, 0 Dietcian, 0 HBAlc, 0 Photometric Glucose, 0 Urine Protiens, 0 Urine dipstix, 0 Electrolytes, 0 Creatinine, 0 Mod Lipogram, 0 Total Cholesterol, 0 LDL

Table IV. Supplier-knowing or supplier abuse

People	Cons	Prcs	Meds	Refs	GP R	Tot R	Tot /GP	Cons /prsn	Procs /prsn	Meds /prsn
9017	16432	11620	2			7373225		1.8	1.3	0.0
1758	4552	1306	7455			2171797		2.6	0.7	4.2
1716	3013	247	0			1267519		1.8	0.1	0.0
1489	2029	80	0			721017		1.4	0.1	0.0
1476	3854	2749	7929			1988895		2.6	1.9	5.4
1415	3683	72	10143			1712910		2.6	0.1	7.2
1256	2884	689	20987			1853135		2.3	0.5	16.7
1084	1942	524	0			867761		1.8	0.5	0.0

Over-prescribing is a frequently seen form of abuse practised by certain categories of providers who self-dispense or have a relationship with medicine suppliers. In the above example the last column indicates the average number of medicines per patient. One supplier of service has seen 1256 people and on average prescribed 16.7 medicines per patient (second from the bottom in Table IV above). In the example below, 115 people received on average 22.1 medicines per patient. (Third from the top in Table V.)

Table V. Number of people, consultations and average number of medicines per patient.

People	Cons	Prcs	Meds	Refs	GP R	Tot R	Tot /GP	Cons /prsn	Procs /prsn	Meds /prsn
21	88	19	0			29188		4.2	0.9	0.0
90	409	70	344			169597		4.5	0.8	3.8
115	473	33	2540			250898		4.1	0.3	22.1
6	27	9	6			12107		4.5	1.5	1.0
4	17	0	22			7905		4.3	0.0	5.5

Alternatively, performing or claiming for fraudulent side-room or hospital admission-procedures can inflate the episode encounter cost. One such example is shown in Table VI below. The supplier of service saw 112 patients, undertook on average eight procedures per patient and prescribed on average 12.4 medicines per patient.

Table VI. Number of people, consultations, procedures and average number of medicines per patient

People	Cons	Prcs	Meds	Refs	GP R	Tot R	Tot /GP	Cons /prsn	Procs /prsn	Meds /prsn
43	44	596	2			224968		1.0	13.9	0.0
1	13	13	34			4284		13.0	13.0	34.0
16	35	154	0			47411		2.2	9.6	0.0
45	148	426	168			71078		3.3	9.5	3.7
14	35	127	15			22926		2.5	9.1	1.1
13	45	119	9			19776		3.5	9.2	0.7
7	5	65	0			37642		0.7	9.3	0.0
112	406	900	1387			366702		3.6	8.0	12.4
1	2	8	0			907		2.0	8.0	0.0
6	4	50	8			4787		0.7	8.3	1.3
5	40	41	28			13492		8.0	8.2	5.6

HEALTH BENEFIT DESIGN

Optimal benefit design is based upon the epidemiology and the help-seeking behaviour of the members. Episodes and encounters form the basis of the help-seeking behaviour tracking. In addition, the following environmental factors help in formulating early, appropriate interventions.

- The known aetiological factors of the presenting conditions.
- Any contributing or aggravating factors.
- The extent of each of the conditions and their geographical distribution within the community.
- The optimal (financial and clinical) points of intervention that will halt the pathogenesis of the condition or the development of complications.
- Integration and timely execution of encounters.

Healthcare benefit design that is based upon claiming patterns alone leads to misuse and abuse. The building blocks of benefit design require an epidemiological assessment of claims data, a demographic assessment of the community, and an understanding of the pathogenesis of commonly occurring conditions and the aetiological factors causing or contributing to the epidemiology. Planning healthcare is an intricate journey of design, adapting basic benefits, applied medical sciences and blending creativity, functionality and experience.

RECOMMENDATIONS

The design of benefits for a health system should always be the combined contribution of a team of stakeholders with all the necessary skills and experience. To avoid misuse and abuse, decentralised management with central monitoring and data interpretation delivers better results than a fixed centrally designed benefit structure. Establishing whether it is misuse or abuse aids in designing appropriate remedial strategies. The former requires education, the latter sanction with unfortunate consequences.

CONCLUSION

Addressing misuse and abuse in healthcare insurance requires a multifaceted and collaborative approach. All stakeholders need to be involved and all have a specific role to play. From the planners where it all starts, to the managers, support services, beneficiaries and suppliers of service. Claims data collection and profiling are required; epidemiologists, demographers, community health specialists and actuaries provide the input to effect cost-efficient design of the benefits. Community health specialists determine the optimal points of intervention to mitigate the cost of neglected clinical symptoms. Management strengthens regulatory oversight. Leveraging technology to assess and evaluate patients' help-seeking behaviours allows for timely interventions to address wayward behaviour. These interventions are aimed at promoting holistic integrated care. The emphasis is on community-based primary care that is integrated with secondary and tertiary care. Monitoring behaviour raises planners' and members' awareness. This is an effective way to combat misuse and abuse. With a concerted effort, a healthcare environment can be built that prioritises patient safety, trust and the ethical provision of sustainable medical services.

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INTEGRATING MENTAL HEALTH and Cardiovascular Risk Management in Type 2 Diabetes Care

Mental health and anthropometric profile targeting individuals with type 2 diabetes mellitus in a private managed healthcare setting

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EXECUTIVE SUMMARY

Major depressive disorder (MDD) is a common type 2 diabetes mellitus (T2DM) comorbidity and is associated with poor diabetes-related cardiovascular disease (CVD) outcomes. MDD is shown to interfere with adherence to T2DM self-care and contributes to poorer diabetes control, more complications and higher healthcare utilisation. The relationship between T2DM and associated comorbidities, particularly MDD and CVD, is poorly acknowledged in chronic disease management practices in South Africa (SA).

The objective of the study was to assess the depressive symptoms and the CVD risk profiles of patients with T2DM.

A cross-sectional study of a sample of members with and without T2DM was conducted for medical scheme members registered between the years 2016 and 2019 in a private healthcare setting. A structured questionnaire, including a Patient Health Questionnaire (PHQ-9), was used to assess possible depressive symptoms and compare anthropometric measures, family history of diabetes and/or heart disease, and smoking status to assess CV risk profiles.

The PHQ-9 scores revealed that patients in the two groups had high levels of depressive symptoms, i.e. mild or moderate-severe depressive symptoms (PHQ-9 scores > 4), with 53.5% and 57.5% in those with T2DM and those without the condition, respectively.

There was no statistically significant difference in the proportion of depressive symptoms between the groups suggesting no association between T2DM and MDD. The majority of individuals in both groups were obese and overweight, with a slightly higher percentage of obesity in the T2DM group (46.4%) than the non-T2DM group (32.5%). Both groups had a strong family history of heart disease or diabetes, (71.4%) in individuals with T2DM and 55.0% and in those without T2DM. Smoking levels were similar between the two T2DM groups at around 16%.

This study highlights the undetected MDD and high CV risk prevalent in a private healthcare setting.

Identifying high-risk CVD individuals sooner, such as those with T2DM, depressive disorders or pre-diabetes, will assist them with self-management of their comorbidities. Managed care programmes should encourage routine screening for depression in all patients.

INTRODUCTION

Approximately, 88.5% of patients with T2DM have two or more comorbidities (Iglay, et al, 2016); (Mata-Cases, et al, 2019), negatively affecting the financial burden and health outcomes of both patients and health systems. In the private managed healthcare arena, non-communicable diseases (NCDs) such as T2DM and mental illnesses such as MDD are seen as discrete endocrine and psychiatric disorders and are typically managed separately.

T2DM is viewed as a CV risk equivalent (Damaskos, et al, 2020; Bertoluci and Rocha, 2017) as hyperglycaemia and insulin resistance increase oxidative stress leading to vascular inflammation, thrombosis and atherogenesis that result in coronary artery disease (CAD) and other cardiac complications (Henning, 2018). Evidence suggests that MDD is a most pervasive mental health illness and a major risk factor for CVD. Correll, et al (2017) report that individuals with severe mental illness (schizophrenia, MDD and bipolar disorder) have 53% higher odds of developing CVD than those without these conditions. However, Inoue, et al (2020) report a higher risk of non-fatal and fatal CVD events among individuals with T2DM and comorbid MDD.

Screening to diagnose and treat MDD in patients with CAD has shown better cardiac outcomes (Yekehtaz, et al, 2013); therefore routine depressive symptom screening is an American Heart Association (AHA) prevention committee and American Psychiatric Association (APA) guideline recommendation to identify patients who may require further assessment and treatment (Lichtman, et al, 2008).

Adverse cardiac outcomes in patients with T2DM and depressive symptoms make this a very-high risk group in the private managed care setting in South Africa (Naidoo, et al, 2019). Naidoo (2024)) suggested the need to understand the bidirectional relationship between T2DM and MDD.

Tools such as the 9-question depression scale from the Patient Health Questionnaire (PHQ-9) that measures depressive symptoms are not actively used within both healthcare sectors in SA for patients with both T2DM and MDD. The PHQ-9 is a validated instrument frequently used in USA primary care clinics (Gilbody, et al, 2007) for all medical illnesses, including in patients with T2DM (Katon, et al, 2004) and in-hospital patients admitted for cardiac conditions (Stafford, et a., 2007).

In South Africa, PHQ-9 is limited to more complex medical illnesses such as HIV/AIDS and is used more often in primary health care clinics (Cholera et al, 2014) and mental health clinics. It is not commonly utilised within the private managed healthcare sector.

This could be for various reasons such as the cost considerations associated with additional resources for a mental wellness programme, lack of awareness, focus on treatment rather than prevention or mental health stigma and privacy concerns.

Other forms of measuring non-invasive CV risk factors include anthropometric measurements such as height, weight, BMI and waist circumference; an immediate family medical history of diabetes and/or heart disease; and lifestyle risk factors, such as cigarette smoking and alcohol consumption. Within the medical scheme environment, these additional key non-invasive CV risk factors are addressed after a CVD event, or when members enrol on discrete disease management programmes, e.g. diabetes mellitus or hypertension or hyperlipidaemia, and are not stringently utilised as screening tools to identify high-risk pre-diabetic members or in the management of MDD and T2DM.

The principles of assessing and managing multiple major risk factors for CVD are critical for preventing macrovascular events such as stroke and myocardial infarction as endorsed by South African (Seedat, et al, 2014) and American guidelines (Arnett, et al, 2019). Hypertension can seldom be managed in isolation from other related chronic diseases, as it often coexists with dyslipidaemia, obesity, glucose intolerance and a family history of early onset. South African guideline recommendations (Seedat, et a., 2014) have broadened the targets of management to include modifiable risk factors, i.e. obesity, smoking, lipids as well as blood pressure control.

AIM

A study was conducted to determine possible undetected symptoms of depression and CV risk factors among patients with T2DM. The objective of this study was to compare the PHQ-9 incidence of depressive symptoms and CVD risk profiles (body mass index (BMI), smoking status and family history of heart disease and/or diabetes) of individuals with and without T2DM.

METHOD

Study design

This was a cross-sectional study carried out from 2016 to 2019 conducted in a private healthcare setting. A structured questionnaire, including a PHQ-9, was used to assess possible depressive symptoms and compare anthropometric measures, family history of diabetes and/or heart disease, and smoking status to assess CV risk profiles.

Sample selection

The 46 000 to 47 380 members of the Chartered Accounts (SA) Medical Fund between 2016 and 2019 were the population for the study. The membership comprises accountants, lawyers and employees of a telecommunication company. The data consist of 136 responses (69 males, 65 females and two undisclosed).

A list of all active members aged ≥18 years were extracted from the scheme's database and the study 'informed consent' and 'questionnaire link' were sent to them. Two groups of patients were identified from the database and categorised as patients with T2DM and without T2DM. International Classification of Diseases and Related Health Problems, 10th revision (ICD1 diagnoses codes E11.0 (T2DM with hyperosmolarity) to E11.9 (T2DM without complications) were used to classify patients having T2DM as stated by their practitioner. The sample included the two groups with and without T2DM who all completed the PHQ-9 and anthropometric questionnaire.

The goal was to collect responses from a sample of beneficiaries of the medical scheme, i.e. 60 responses from each group of individuals with and without T2DM between the years 2016 and 2019. The sample size for this study was determined based on a similar study done in Ghana, which had a sample size of n=29 per group, calculated based on a difference of 36% in PHQ>= 5 between T2DM+MDD vs T2DM-MDD groups; 31.3% of Ghanaians with T2DM are reported to have depression (Akpalu, et al, 2018) with an 80% power and a type I error of 5%.

Procedure

A standard letter explaining the purpose and benefits of the research was sent each year to all scheme members via email. Participants were told that the study was designed to investigate the relationship between diabetes and depression in the private healthcare sector in SA. The benefits were to contribute to medical knowledge that may help other individuals with MDD or T2DM. Participants were advised on the informed consent form that the questionnaire would assist in recognition of possible depressive symptoms; they were advised to contact their doctor to assess them for depression and, if necessary, initiate treatment.

Informed consent. Participants gave informed consent after they were advised of the confidentiality of any sensitive information, and that only unique membership numbers would be used in the analysis. The consent from the members to participate in the study was obtained electronically.

Follow through. Participating patients were contacted via email and telephone as a reminder. Research assistants (i.e. in-house scheme pharmacy assistants, nurse case managers and customer care agents) assisted by guiding members telephonically through the process of accessing the questionnaire link.

The PHQ-9 (Levis, et al, 2019) was used to screen and diagnose depression and has been validated in the sub-Saharan African population (Adewuya, et al, 2006, Weobong, et al, 2009);van Steenbergen-Weijenburg, et al, 2010). It helps healthcare professionals identify signs or symptoms of depression based on the scoring results of the PHQ-9 statements and is a mandatory part of healthcare management in the USA for regular depression screening during primary care check-up (Siu, et al, 2016). The components of the PHQ-9 test evaluate factors related to depression according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (Nuckols, 2013).

A self-reporting structured questionnaire was created in a secure platform: Research Electronic Data Capture (REDCap) (Harris, et al, 2009). The data were automated to download onto Excel and then captured and analysed. The REDCap questionnaire is included as an addendum. Data were collated for members who completed the form once during the years 2016-2019. Duplicate entries for those members who completed it more than once were removed.

ETHICAL CONSIDERATION

Confidentiality was maintained throughout the analysis; all information obtained during the course of the study was reviewed by the authorised researchers on secure laptops using password protection; patients' unique scheme membership numbers and dependent codes were used to align patient-level records. The University of the Witwatersrand's Faculty of Health Sciences Human Ethics Committee (M140326; M1911196) approved the study. Further approval for use of scheme data was granted by the Principal Officer of the scheme. The Human Resources Manager approved the gathering of data from the scheme's administrative database for the research.

STATISTICAL AND DATA ANALYSIS

Data were exported to Microsoft Excel 2016 and statistical analysis was performed with Statistica 13.3 (StatSoft Inc., Tulsa, OK) and SAS 9.4. Categorical variables such as sex, BMI, PHQ-9 and CV risk factors were summarised as frequencies and percentages and compared using Chi-square or Fisher-exact tests. A significance level was set at 0.05.

Patients' PHQ-9 scores were categorised according to symptoms experienced, i.e. <5 minimal symptoms not requiring antidepressants; 5-9 mild and ≥10 moderate to severe depressive symptoms (Kroenke, et al, 2001). Patients were grouped into BMI categories: normal range with a BMI of 18.5-24.9, overweight with BMI between 25 and 29.9, and obese with BMI ≥30.

RESULTS

Table 1 displays the characteristics of individuals with T2DM and without T2DM. The individuals without T2DM were significantly (<0.0001) younger (48+/-14.6) and there was a greater proportion of females [55% (one undisclosed)], whereas the T2DM group had more males (60%) and were older (60 +/-12.9).

The proportion of depressive symptoms (mild and above) was similar for those with and without T2DM (53.5%; 57.5%), with both groups having moderate-to-high depressive symptoms of 32.1% and 33.8%, respectively.

Although there was no statistical association between T2DM and BMI, the percentage of individuals classified as obese was more than marginally higher among individuals with T2DM (46.4%) than those without T2DM (32.5%). The percentage of individuals classified as having normal BMI was 12.5% and 25% for those with T2DM and those without the condition, respectively, indicating high levels of overweight and obesity among study participants.

The percentages of family history of heart disease and/or diabetes were high among those with T2DM (71.4%) compared to those without (55%). However, there was not enough evidence to suggest a statistical difference: CI=2.05 (0.988-4.23). A larger sample size would possibly show a difference. There was no difference in the levels of smoking between the two groups: about 16% for both the T2DM and no-T2DM groups.

Table 1: Characteristics of Individuals with and without T2DM: 2016-2019

Characteristics	Individuals with T2DM n=56 n (%)	Individuals without T2DM n=80 n (%)	p-value
Age (y) (mean±SD)	60 +/-12.9	48+/-14.6)	<0.0001
Sex (male)	33 (60%)	36 (45%)	0.11
MDD (PHQ-9 score) <5 5 – 9 ≥10	 26 (46.5) 12 (21.4) 18 (32.1)	 34 (42.5) 19 (23.75) 27 (33.75)	0.896
BMI <25 BMI 25-29.9 BMI ≥30 (Obese)	7 (12.5) 21 (37.5) 26 (46.4)	20 (25) 28 (35) 26 (32.5)	0.120
CV risk factors			
Smoker	9 (16)	13 (16.3)	0.978
Family history of heart disease/diabetes	40 (71.4)	44 (55)	0.052

BMI, Body Mass Index; MDD, Major Depressive Disorder; T2DM, Type 2 Diabetes Mellitus; Patient Health Questionnaire (PHQ-9) score ranges from 0 (best) to 27 (worst); score 5-9 indicates mild depressive symptoms; score ≥10 indicates moderate to severe depressive symptoms; BMI of 18.5 to 25 is within the normal range, BMI between 25 and 30 is within overweight range, BMI ≥30 falls within the obese range.

DISCUSSION

The main findings of the study showed that individuals with and without T2DM both had high levels of mild-moderate to severe depressive symptoms, but there was no evidence of an association between depressive symptoms and T2DM.

The findings showed slightly lower levels of moderate-severe depressive symptoms among individuals in the T2DM group (32.1%) compared to a previous study by (Binsaleh, et al, 2018) where 53% of individuals with T2DM taking antidepressants had moderate-severe depressive symptoms.

Depressive symptoms (PHQ-9 score >4) among patients with T2DM (53.5%) and without T2DM (57.5%) were high in this setting. Our study showed similar rates of depressive symptoms among those with and without T2DM. In another study, people with T2DM have twice the odds of presenting with MDD (19.1% vs 10.7%) compared to those without T2DM (Roy and Lloyd, 2012), contrary to our study, which has an unadjusted odds ratio of 0.93. Higher rates of depression have been reported among adults with T2DM in urban centers of Pakistan (43.5%) (Khuwaja, et al, 2010) and in Iran (72%) (Khamseh, et al, 2007). In contrast to our findings, a meta-analysis reported 31% of T2DM patients were diagnosed with depression (Anderson, et al, 2001). Studies in Africa report that the prevalence of depression among patients with T2DM ranges from 19.4% to 30% (James, et al, 2010). In Ghana 31.3% of T2DM patients presented with depression (Akpalu, et al, 2018). Lower rates of depression were found in studies in the UK (25%) (Collins, et al, 2009) and even lower rates in the USA (8.3%) (Li, et al, 2008). A possible reason for the high rates of MDD among the individuals in our study could be explained by the small sample size, differences in their socioeconomic cultural background and different assessment tools.

Of concern was that almost 60% of individuals without T2DM presented with depressive symptoms. Active surveillance is necessary to identify these individuals sooner and refer them for management or treatment of MDD. The present study showed that patients with T2DM and without T2DM have a high rate of underlying unrecognised depressive symptoms. Patients in this private healthcare setting might work in highly stressed professions, and this might be the reason for the high levels of depressive symptoms, as has been reported among the accounting profession (Donald, 2021).

Patients in this study presented with significantly high BMIs. It is known that weight gain is an adverse effect associated with certain antidepressants, i.e. selective serotonin reuptake inhibitors, serotonin norepinephrine reuptake inhibitors and serotonin receptor antagonists and reuptake inhibitors (Gelenberg, 2010). In a previous study (Naidoo, 2024), 48% of the patients in this managed healthcare organisation were noted to be on SSRIs, which may have an influence on their BMI, as seen in these sample groups where the BMI was high.

Healthcare providers (psychiatrists, physicians, diabetes nurse educators and dietitians) can assist patients with their treatment plans in adhering to Society for Endocrinology, Metabolism and Diabetes of South Africa (SEMDSA) guidelines (Amod, 2017). These recommend healthy diets, physical activity and choice of appropriate antidepressant (Gelenberg, 2010); (Emsley, et al, 2013) that suits the patient.

Obesity or being overweight was noted among individuals in both groups in this setting, which shows the existing burden in SA (Nglazi and Ataguba, 2022) and worldwide (Cois and Day, 2015); (Ng, et al, 2014). Clearly, poor diet and an unhealthy lifestyle represent a challenge, and they compromised by depressive symptoms, as one consumes more calories than the amount expended when the mood is low (Fock and Khoo, 2013); (Jacka and Berk, 2013).

The risk of T2DM is higher among obese individuals (Schnurr, et al, 2020) with or without MDD. Poor glycaemic control, depressive symptoms and non-invasive CV risk factors could also influence the aetiology of MDD on T2DM (Lustman and Clouse, 2005);(Hamieh, et al, 2019).

In addition, obesity adds to the burden as a comorbidity to T2DM and MDD and as a CVD risk factor. Decision-makers and policymakers need to update policies, protocols and resources to bridge the gap between depressive symptoms and clinical profiles (BMI, smoking status) among individuals with endocrine disorders and psychiatric disorders, i.e. T2DM and MDD. Policies should incorporate the structured PHQ-9 together with anthropometric measures at routine health appointments as standard of care.

Undetected depression in T2DM and undetected indicators of CV risk inT2DM patients worsen their long-term mortality risks (Damián, et al, 2017). The foundation of managing T2DM revolves around encouraging a lifestyle that incorporates a balanced diet, regular physical activity, quitting smoking and maintaining a healthy body weight (Aschner, 2017). Therefore, early stringent screening for and management of depressive symptoms and non-CV risk indices are paramount in this private setting, to reduce the risk of non-fatal and fatal CVD events among patients with T2DM.

LIMITATIONS

The sample size of the study was relatively small; therefore, the study may not be sufficiently powered to see any statistical differences and associations between groups. Data on abdominal measurements, alcohol consumption, behaviour and physical exercise and non-compliance with medication, factors that may be associated and/or modify the relationship between T2DM and MDD, were not captured and therefore could not be assessed.

CONCLUSION

The findings of this study showed that MDD is common among individuals in this private managed healthcare setting. Depressive symptoms were not associated with T2DM in our study. Individuals with or without T2DM were mostly overweight and obese. Active surveillance of non-invasive CV risk factors, depressive symptoms, non-invasive body measurements and lifestyle surveys in patients with T2DM and individuals joining the scheme is critical. Making this mandatory every six months, during their regular check-ups with their physicians to identify, treat and manage T2DM, MDD, or pre-diabetes and depressive/stress symptoms sooner, may be necessary. Future studies need to look at the level of glycaemic (HbA1c) control in individuals with and without T2DM.

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ADDENDUM 1

Definitions of relevant concepts discussed in this article

TERM/CONCEPT	DEFINITION
PHQ-9 The PHQ-9 is a component of the Patient Health Questionnaire and includes nine short, simple questions that can be self-administered and completed in 5-7 minutes.	Patient-Health-Questionnaire (PHQ-9) is used to screen for and diagnose depression. Patient-Health-Questionnaire (PHQ-9) is used to screen for and diagnose depression. The components of the PHQ-9 test evaluate factors related to depression according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), and include low mood, anhedonia, feelings of hopelessness, sleep and appetite issues, a lack of energy, irritation, difficulty concentrating and suicidal ideation. Each question is presented as a statement and asked how often the feelings were experienced in the past 2 weeks. The PHQ-9 scores are assigned 0 to 3 points (0 - not at all, 1 - several days, 2 - more than half of the days, 3 - nearly every day) for the symptoms experienced.
REDCap (Research Electronic Data Capture (REDCap). The REDCap structured questionnaire created is available as an addendum.	A self-reporting structured questionnaire was created in a secure platform: REDCap. The questions included demographics, history of T2DM and MDD, and PHQ-9 assessment of specific symptoms over the past 2 weeks; non-invasive CV risk factors, i.e. anthropometric measure such as height and weight, BMI, waist circumference; smoking status, immediate family history of diabetes and/or heart disease. The data were automated to download onto Excel and were then captured and analysed.
BMI (Body Mass Index)	BMI is a medical screening tool that measures the ratio of a person's height and weight to estimate the amount of body fat. It can help assess risk factors for metabolic syndrome, T2DM and CVD.

ADDENDUM 2: THE REDCAP QUESTIONNAIRE

Examining the bidirectional relationship between depression and type 2 diabetes

I would like to invite you to participate in a research study, entitled: Examining the bidirectional relationship between comorbid depression and type 2 diabetes: A managed healthcare perspective.

Your participation in this study will contribute to medical knowledge that may help other individuals that have Depression or Type 2 Diabetes.

In anticipation.

Yours sincerely,

Lovina Naidoo

Before you agree to participate in the study, it is important that you read and understand the Information Leaflet and Informed Consent.

[Attachment: "Informed consent non-depressed group.docx.pdf"]

Informed consent non-diabetic group.

[Attachment: "Informed consent non-diabetic group.docx.pdf"]

If you decide to take part in this study, please sign using your finger (touch screen) or the mouse here.

_____

Please acknowledge that by completing this survey you are consenting to participate in this survey as described in the above introduction and the attached document. Do you consent to participate?	◯ Yes ◯ No

---

I hereby agree that I will have the following blood tests within the next four weeks: - Blood glucose - Cholesterol and Blood Pressure	◯ Yes ◯ No

---

Attached is the Lancet blood work up form for your convenience. You may include the name of your doctor on the top right corner of the form.

[Attachment: "CAMAF Diabetes Tests-Lancet Order Form.pdf"]

ADDENDUM 2 (CONTINUED)

Demographic Information	
Medical Aid Number	_____
Dependent Code	_____
Date:	_____
Age:	_____
Gender	◯ Male ◯ Female
Have you been diagnosed with Type 2 Diabetes?	◯ Yes ◯ No
When were you diagnosed?	_____
Have you been diagnosed with Depression?	◯ Yes ◯ No
When were you diagnosed?	_____
Is there a history in your immediate family of either diabetes or heart disease?	◯ Yes ◯ No
What is your height in centimetres (e.g. 172)	_____
What is your current weight?	_____
Your Body Mass Index is:	_____
What is your waist circumference in centimetres?	_____
Are you currently a smoker?	◯ Yes ◯ No

ADDENDUM 2 (CONTINUED)

PATIENT HEALTH QUESTIONNAIRE (PHQ-9) **Over the last 2 weeks how often have you been bothered by any of the following problems? (Click the circle to indicate your answer)**	
1. Little interest or pleasure in doing things	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
2. Feeling down, depressed, or hopeless	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
3. Trouble falling or staying asleep, or sleeping too much	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
4. Feeling tired or having little energy	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
5. Poor appetite or overeating	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
6. Feeling bad about yourself -- or that you are a failure or have let yourself or your family down	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
7. Trouble concentrating on things, such as reading the newspaper or watching television	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
8. Moving or speaking so slowly that other people could have noticed? Or the opposite -- being so fidgety or restless that you have been moving around a lot more than usual	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
9. Thoughts that you would be better off dead or of hurting yourself in some way	◯ Not at all ◯ Several days ◯ More than half the days ◯ Nearly every day
If you checked off any problems, how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people?	◯ Not difficult at all ◯ Somewhat difficult ◯ Very difficult ◯ Extremely difficult

TRANSFORMING PUBLIC HEALTH with Medicine Shelf-Life Extension

AUTHOR

Precious Ncayiyana

PEER REVIEWER: Jacques Snyman

EXECUTIVE SUMMARY

Background

Large quantities of scheduled substances are destroyed annually by the public healthcare sector of South Africa. This poses an ethical dilemma – many of these agents are taken off the shelf while still meeting all specifications as well as stability requirements.

The Shelf-Life Extension Programme (SLEP) was established in the USA in 1986 (FDA, 2023). The programme resulted from the realisation that in order for the government to successfully stockpile medicines to ensure adequate supply during a public health emergency, for both the military and its private citizens, an extended shelf-life is required for those drugs.

The FDA, through its Emergency Use Authorization programme, has authorised the use of Tamiflu® capsules in strategic stockpiles. The agent may be administered for a maximum of 20 years, provided recommended storage conditions are maintained.

Purpose

To explore the use of a similar programme to minimise costs and wastage associated with the disposal of scheduled substances that have passed their published expiry date, as printed on the packaging.

Method

This study is classified as an observational study based on the ordering, dispensing and disposal of drugs in a public healthcare facility. Data were obtained from a pharmaceutical disposal schedule within the facility.

Results

Literature review supports shelf-life extension for approximately 90% of agents tested, with an average extension period of 66 months based on the SLEP. The consensus is that the SLEP should be applied to tablets and capsules as they are regarded as more stable than liquids.

INTRODUCTION

Large quantities of scheduled substances are destroyed each year by public health institutions across South Africa. This costs the taxpayers of South Africa millions. It poses a large ethical dilemma; some drugs are taken off the shelf while still meeting all criteria in respect of their specifications and stability requirements. This paper proposes that a programme, through a government and/or South African Health Products Regulatory Authority (SAHPRA) initiative, be introduced to test scheduled substances, which include tablets, capsules, dry powders and powders for injection, for stability in order to extend their expiration date by at least 12 months,

In 1986, the USA military and the Food and Drug Administration (FDA) established a programme called the Shelf-Life Extension Program (SLEP). The aim of the SLEP was to reduce the cost to the government by avoiding the need to replace entire stockpiles of medicines every few years through the testing of certain products that remained stable beyond their labelled expiration date when properly stored (FDA, 2023). The programme resulted from the realisation that for the government to successfully stockpile medicines to ensure adequate supply during a public health emergency, for both the military and private citizens, an extended shelf-life is required.

Medicinal product shelf-life (expiration date) extension, in South Africa, is a common practice performed typically by the manufacturer of said agent. The affordability of drugs remains a challenge for the African continent along with many other parts of the world. The expiry date of an agent is not the true indication of the point at which the medication is no longer effective or safe for use; instead, the expiry date is defined as the final point at which the manufacturer guarantees full potency and safety of the product (Gikonyo, et al, 2019) and is often a regulatory cutoff. When medication is stored according to manufacturer specification, the agent is able to remain effective, safe and within specification for an extended period of time. A study by the FDA, at the request of the military, demonstrated that 90% of drugs tested were effective and in adequate condition for use for another 15 years after the given expiration date (Gikonyo, et al, 2019).

Through the Emergency Use Authorization programme, the FDA has authorised the use of Tamiflu® capsules in strategic stockpiles for a maximum of 20 years, provided the recommended storage conditions are maintained (FDA, 2023). Tamiflu® (oseltamivir) is indicated for the prophylaxis and treatment of influenza A as well as influenza B in both adult and paediatric populations (Genentech, 2012). This forms the basis for the author's proposal to explore shelf-life extension of drugs deemed essential for the South African population.

Study design

Purpose

a. To explore the use of a similar programme to minimise the costs and wastage associated with the disposal of expired scheduled substances.

b. To aid in the extension of the shelf-life of usable drugs.

Methodology

This study is classified as an observational study, based on the ordering, dispensing and disposal of drugs in a public healthcare facility. Data were obtained from a pharmaceutical disposal schedule within the facility.

1. THE IMPORTANCE OF THE SLEP

The SLEP will reduce the cost to the military of the maintenance of stockpiles of certain pharmaceuticals, stocks that are currently non-existent due to the short expiry dates of the current medication system. The SLEP will assist in the stockpiling of medicines deemed essential for the military as well as the citizens of South Africa. In other public institutions, reasons for introducing a SLEP may vary, but mainly revolve around keeping sufficient supplies of medicines deemed essential and to minimise discarding drugs that are still efficacious and safe for human consumption. This makes a SLEP important for both the military and the general public.

2. ESTIMATED COST OF DISPOSAL

According to the South African Pharmacy Council's rules and regulations, the disposal of medicines should be performed within 90 days after the expiry date. In public facilities it is difficult to adhere to this timeline as a result of procurement challenges.

The following is an example of one of the invoices for pharmaceutical waste disposal from one supplier in 2020:

a. 20-litre pharmaceutical waste buckets cost ZAR86.00 per bucket. The organisation required a total of 100 buckets for this disposal.

b. Lids for the buckets cost ZAR22.00

c. Pharmaceuticals were charged at ZAR35.00/kg and the organisation had 6000kg in total to dispose of.

d. Originator's alteplase, which is indicated for acute myocardial infarction: one 50mg vial costs R10 253.73 [single exit price] (MIMS, 2023).

The aforementioned items excluded value-added tax (VAT) as the organisation is VAT exempt. The total equated to an astounding ZAR220 800.00. For public-funded institutions, more drugs could be procured with this type of money. It should also be noted that the value of the items disposed of was not disclosed. However, it is common knowledge that pharmaceuticals are expensive; 6000kg of various pharmaceuticals could easily cost up to a few million rand. Based on the cost of alteplase per vial, 100 vials which is equivalent to 5000mg will cost roughly R 1 025. 373. This means that 1000g of alteplase could easily cost over R205 million. This illustrates the actual cost of pharmaceuticals over and above the disposal cost.

3. DRUGS TESTED THROUGH THE SLEP

The following table gives examples of some of the drugs that were tested and assigned an extended shelf-life by the FDA, as extracted from Diven, et al (2015). The examples chosen include dry powders and solutions, which are widely used as first-line treatment in primary and emergency care in South Africa. Their unavailability may have undesirable healthcare outcomes.

The agents above form part of South Africa's essential medicine list. However, there are many more substances not included in this list that are deemed essential for our population, such as agents for the treatment and management of tuberculosis and antiretroviral drugs.

Table1: Products which can be targeted in the South African market.

MEDICATION	FORM	MONTHS EXTENDED
Amoxicillin sodium	Tablets	23
Dobutamine HCl	Injection solution	47
Ampicillin	Capsules	49
Doxycycline hyclate	Capsules	50
Promethazine HCl	Injection solution	51
Ringer's, lactated and dextrose	Injection solution	53
Ciprofloxacin	Tablets	55
Ampicillin sodium	Injection solution	57
Mebendazole	Tablets	58
Ceftriaxone sodium	Powder	60
Phenylephrine HCl	Injection solution	60
Ketamine HCl	Injection solution	64
Protamine sulfate	Powder	64
Dextrose (5%)	Injection solution	65
Fentanyl citrate	Injection solution	84
Bupivacaine HCl	Injection solution	88

4. RESULTS AND DISCUSSION

The observation within the military facility noted the fact that many drugs, especially in government institutions, expire as a result of logistical challenges. Public health facilities order in bulk, which compounds the drug expiration problem.

The public sector lacks a more agile inventory management system, which would allow for institutions to order drugs only as they are needed in order to increase efficiency and reduce wastage (Watts, 2023). As a result, there is a large volume of drug wastage throughout the government pharmaceutical supply chain. Drugs that expire at depots and facilities place an additional financial burden on the public purse.

This may be curtailed by implementing a SLEP. Literature supports that about 90% of drugs tested had an average extension period of 66 months further to the introduction of the SLEP (Gikonyo, et al, 2019). The consensus is that a SLEP should be primarily applied to tablets and capsules, as they are more stable than liquids.

At the start of the SLEP the FDA was very conservative about granting extended shelf-lives. The maximum extension given was up to three years beyond the initial expiration date (FDA, 2023). In the early 1990s, the programme grew considerably, and it continues to grow as new drugs are discovered, deemed important and then added to the SLEP. The programme now has participants outside the USA's Department of the Defence, consequent on its recognised value, validity and credibility. Additionally, it is executed in conjunction with the FDA. It is continually being updated and is strictly implemented to ensure the safety and efficacy of all products tested.

In South Africa, in both the military and public sector, pharmacists have expressed huge interest in the programme. The following are a number of points that have been noted:

a. The cost associated with disposing of expired stock is enormous, A SLEP may be the answer.

b. The abandonment of government incinerators has led to the ever-increasing cost of outsourcing medical waste, and yet the budget keeps shrinking.

c. The short-dated stock of essential medications deemed critical for managing infectious diseases like resistant tuberculosis is problematic.

South Africa should prioritise piloting the concept of a SLEP. If utilised effectively and responsibly it has the potential to reduce costs associated with disposal of drugs that are deemed safe and efficacious for human consumption, because of uncertainty and fear of litigation. Africa is deemed a third-world continent logistically and financially. This initiative may inspire other countries in Africa to pursue a similar strategic programme.

5. ETHICS OF DISPOSING OF EFFICACIOUS DRUGS

Morals are about what is right and wrong, and medical ethics deals with the rights and wrongs of decision-making in clinical practice (Markose, et al, 2016). Medical ethics are defined as principle-based ethics, stemming from 'principlism', which is the foundation for ethical decision-making popularised by Beauchamp and Childress (2001).

Principlism encompasses the following principles: beneficence, non-maleficence, autonomy and justice. The applicable principles in this case are the principles of justice, otherwise known as the principle of fairness and non-maleficence. Non-maleficence, a principle of 'Do No Harm', asserts an obligation not to inflict harm intentionally. By disposing of medication that is still safe and efficacious for human use, we could be inflicting harm on patients, though not intentionally. The harm to the patient may come in the form of non-compliance, progression of disease or infection, or abandonment of treatment, for example.

The applicable principle of justice in this case, could be distributive justice. This form of justice refers to the extent to which society's institutions ensure that benefits and burdens are shared among society equitably in a fair and just manner (Andre and Velasquez, 2014). The principle of distributive justice places an obligation on health institutions to consider any means like the SLEP that may aid in the reduction of the cost burden and also widen access to medication for the general population.

6. CONCLUSION

A specialised programme to extend the shelf-life of tablets, capsules, dry powders and powders for injection is highly recommended. This will assist military deployments and the South African government in ensuring an adequate supply of critical drugs in times of humanitarian crisis. It will also aid in the reduction of waste and unnecessary expenditure due to the destruction of drugs that may still be safe for human consumption.

7. RECOMMENDATIONS

It is recommended that the South African Military Health Service's Surgeon General leads the pilot SLEP for the military. The drugs to be utilised for the pilot testing will include agents deemed critical in both the military and the public sector.

8. LIMITATIONS AND FUTURE RESEARCH

The literature review is limited to the US military and FDA. There are speculations that there may be other militaries in other countries embarking on similar SLEPs privately.

Future research should include expansion of the programme beyond dry powders to include lifesaving drugs like injectable insulin and anti-venoms.

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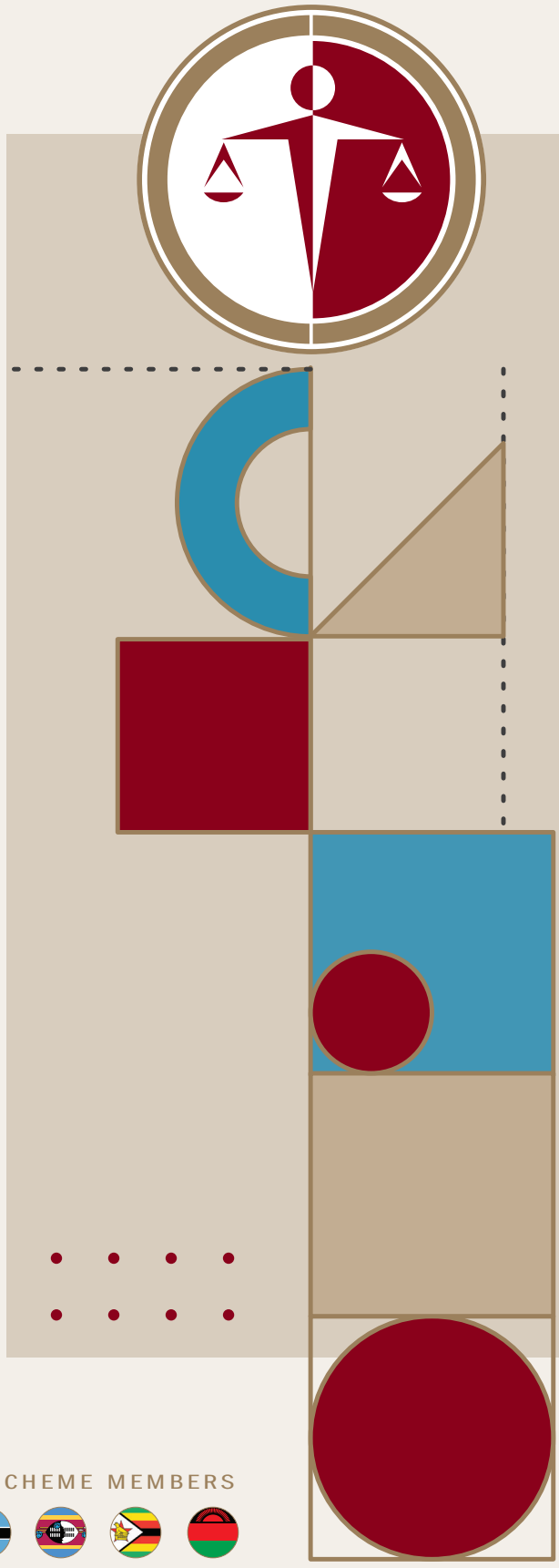

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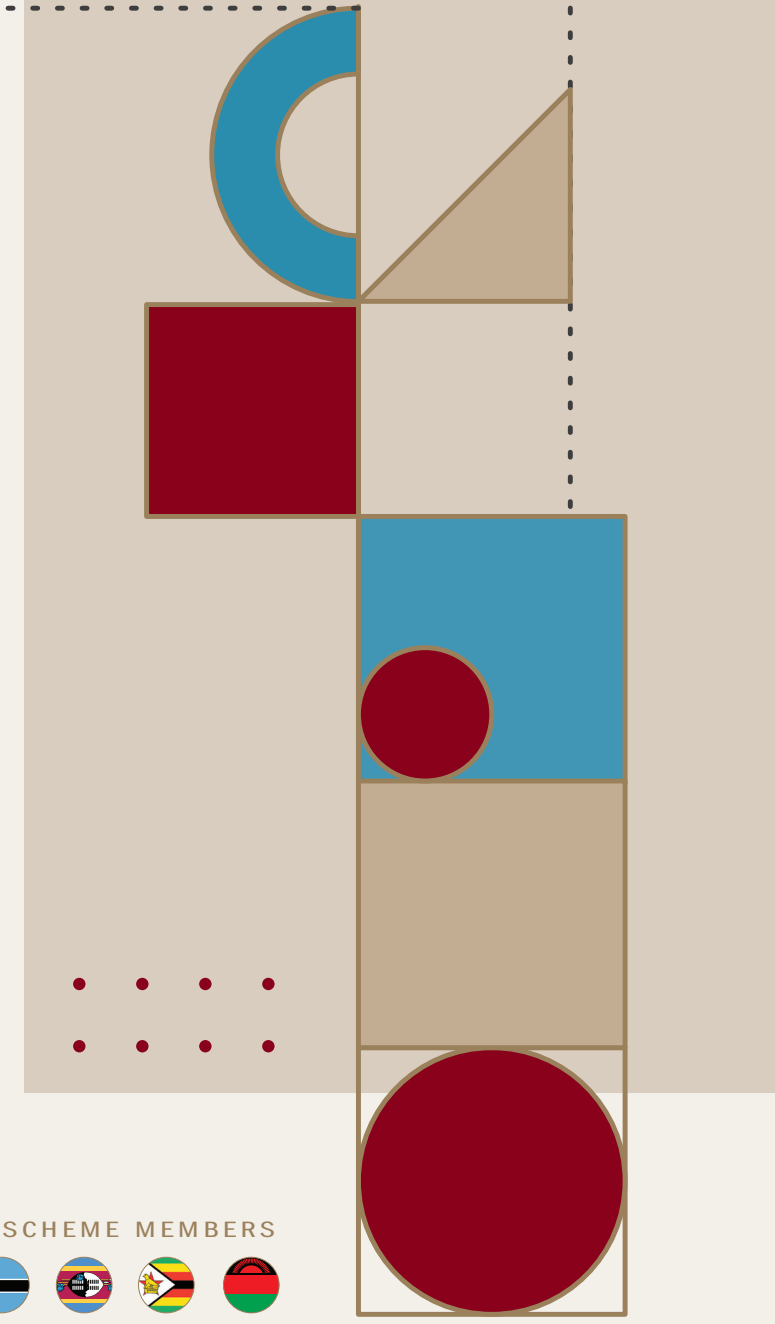

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