

Introduction

Rising mental healthcare expenditure, driven by increasing incidence and prevalence, is placing growing pressure on health systems globally, and is further complicated by evolving socioeconomic factors [1]. Managed care interventions that are not carefully aligned with patient needs and system capacities may unintentionally compromise the quality of patient care and contribute to worsening financial strain. To address this challenge, healthcare organizations are adopting Value-Based Healthcare (VBHC) models, which incentivize providers to prioritize patient health by linking reimbursement to health outcomes rather than service volume. This approach has shown potential to improve outcomes across chronic diseases [2]. To be effective, VBHC models must integrate evidence-based interventions at appropriate intervals for early identification to prevent disease onset. However, this has not yet been clearly demonstrated, particularly in addressing the needs of marginalized populations [3].

Achieving outcome and cost measurement at individual case level while maintaining compliance and adaptability requires innovative approaches [4,5]. These approaches must support data collection and analysis across clinical conditions and care cycles, generating stratified insights to guide targeted reimbursement strategies. Accurate measurement of resource use within such a system is crucial for identifying the most appropriate reimbursement models for specific conditions and population groups. Therefore, integrating technological innovations into VBHC design is essential to define measures that ensure consistency and comparability across populations, physiological factors, systems, and regions. This level of specialization is critical for accurately assessing and comparing healthcare outcomes within stratified populations—a fundamental requirement of effective VBHC models. Although this information is known, the effective implementation of these approaches has not been demonstrated.

Objective

The integration of technological innovations into VBHC design is essential to systematize measures that ensure consistency and comparability across diverse populations, health systems, and regions. Such systematization is crucial for accurately assessing and comparing healthcare outcomes within stratified populations – a core principle of VBHC. The presented research aims to provide a framework for stratified risk-adjusted clinical management based on claims data.

Methods

The presented research is premised on an analytical research methodology that applies a structured, systematic approach to investigate, interpret and explain, and dissect the study data by examining its components and the relationships between them (Fig. 1).

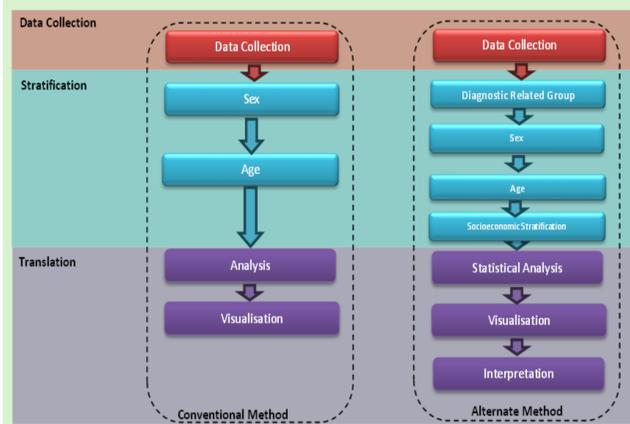


Figure 1: Comparison between conventional and alternative data analysis. The alternate data analytical method provides a systematic approach aimed at measuring the true burden of mental health conditions to allow for precision strategic managed care strategies to be implemented.

The Insight Data Universe, comprising an aggregated dataset of over 3.5 million insured beneficiaries from multiple Funds, was systematically analyzed for Mental Health Diseases and Disorders admissions in 2024 using the Insight Diagnosis-Related Grouper (DRG). All data was fully de-identified and anonymized to ensure that no individual Fund or beneficiary could be identified. Analyses were conducted on aggregated information. De-identified claims were stratified by age, gender, socioeconomic status, and clinical diagnosis, with socioeconomic status based on salary income bands (Low, Middle, High). Statistical comparisons used one-way ANOVA (non-parametric), the Friedman test, and the Benjamini–Krieger–Yekutieli procedure to control the False Discovery Rate.

Results

A total of 1,978,538 aggregated and fully anonymized mental health claims records were analyzed, representing a total expenditure of 138,756,648 USD (approximately 18% of annual mental health expenditure in South Africa). Data were drawn from multiple funds, ensuring no single client Fund's data was identifiable. Further analysis of the data indicated that the middle- and high-income earners' claims were significantly higher in comparison to low-income earners (Fig. 2).

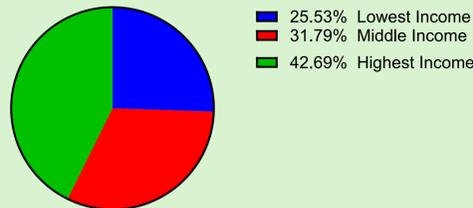


Figure 2: Data Distribution of Male and Female patients classified according to total risk claims by total contribution. This figure illustrates the percentage distribution of the risk claims by members according to age and sex.

The risk claims data was first ordered according to gender and age (Fig. 3). It is observed that females within the 40-59 age group constituted 37.83% of the total claims by value, while the 40-59 male group contributed 13.8% (Fig. 3). The 20-39 year female group was the second highest contributor with 14%.

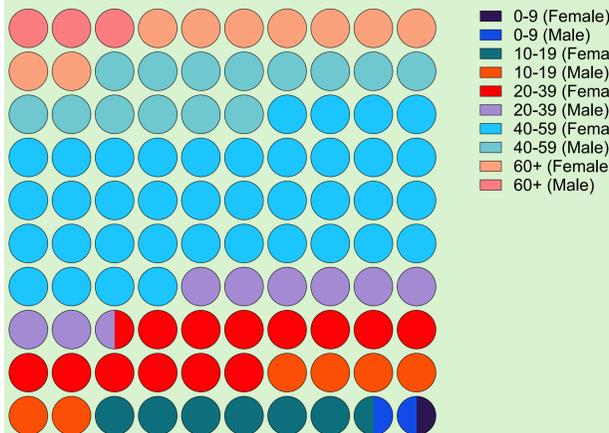


Figure 3: Data Distribution of Male and Female Patients classified according to total risk claims by total contribution. This figure illustrates the percentage distribution of the risk claims by members according to age and sex.

Figure 4 illustrates the statistical distribution of claims across the risk groups. It can be observed that female claims expenditure was higher than that of males relative to the total mental health expenditure across groups. The 40–59-year female age group contributed to a significantly higher mental health expenditure, with a high probability distribution of claims within the higher expenditure range.

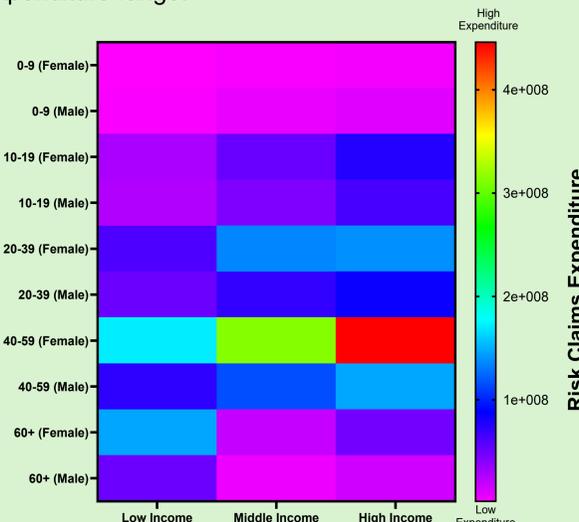


Figure 4: Heatmap indicating the stratified distribution of risk claims classified according to gender, age, and income band. This heatmap can be used to easily classify risk groups within a selected population.

Although ANOVA analysis indicated that there is a statistically significant difference between groups ($p < 0.03$), the two-stage linear set-up procedure of Benjamin, Krieger, and Yekutieli FDR test indicated that there is a significant discovery between High vs. Low Income ($q < 0.02$; $p < 0.01$) and High vs. Middle income ($q < 0.04$; $p < 0.04$). This indicates that there are socioeconomic disparities between these groups that is influencing the claims expenditure. However, the test reveals no significant discovery between the middle vs. low income bands ($q < 0.43$; $p < 0.61$). This indicates that the socioeconomic disparities between these two groups comprise of similar factors that are driving expenditure. The top contributing risk group (i.e. 40-59 year old Females) was further stratified according to ICD-10 codes within the Mental Health Diseases and Disorders using the Insight Diagnosis-Related Grouper (Fig. 5).

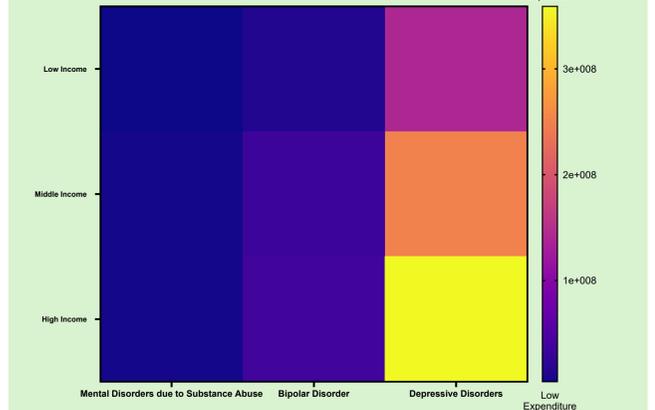


Figure 5: Heatmap indicating the stratified distribution of risk claims classified according to the top 3 ICD contributors and income band within the 40-59 year female risk group. This heatmap can be used to easily identify top diagnostic risk contributors within a selected population.

ANOVA analysis of claims data indicated that there is no statistical significance between income groups ($p > 0.05$) and a statistical significance between diagnostic groups ($p < 0.02$). The two-stage linear set-up procedure of Benjamin, Krieger, and Yekutieli FDR test indicated that there is no significant discovery between income bands ($q > 0.05$), with a significant discovery between mental disorders caused by substance abuse vs. depressive disorders ($q < 0.03$; $p < 0.01$). Importantly, this analysis indicates the progressive increase in depressive disorder expenditure from low to high income groups ($> 50\%$). These findings indicate that the socioeconomic impact within the group is closely associated with clinical factors, in which managed care interventions must be personalized according to the diagnosis across salary bands.

Conclusions

This study demonstrates that identifying clinical and socioeconomic risk factors within a population can help pinpoint high-risk patient groups and may support the development of personalized, value-based healthcare programs tailored to the specific needs of these groups. The findings of this study, when integrated into a VBHC model based on a stepped care approach (Fig. 6), could lead to positive outcomes. Statistically validated analyses are crucial for informing reimbursement models that encourage high-quality, cost-effective, and coordinated care, ultimately improving healthcare decision-making.

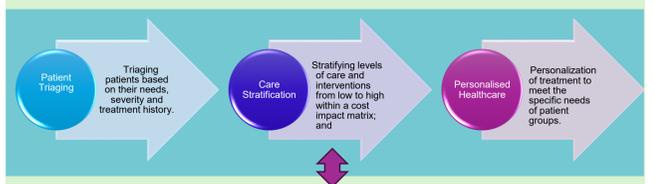


Figure 6: Stepped care model for management of mental health disorders informed by stratified data analytics.

Acknowledgments

Insight thanks the South African Government Employees Medical Scheme (GEMS) for their collaboration and contribution to this study, and for their commitment to advancing pragmatic healthcare research.

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