

Portfolio



Luis Bolanos, MSc **Healthcare Data Analyst**

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Turning healthcare data into actionable insights for smarter decisions.

About me:

I am a Healthcare Data Analyst with 20+ years of experience turning complex public-health and clinical datasets into actionable insights. I specialize in statistical analysis, data visualization, and decision-support reporting using Excel, Power BI, and Tableau. My background includes epidemiology, population health, and national-level monitoring systems. I am based in Florida and focused on supporting healthcare organizations to improve efficiency, quality, and patient outcomes.

My skill set

- ❑ **Data Acquisition & Integration:** Source and consolidate healthcare datasets (EHR, claims, operational data) to support performance improvement and clinical decision-making.
- ❑ **Data Cleaning & Transformation:** Ensure data accuracy, consistency, and compliance with privacy standards for analytical readiness.
- ❑ **Descriptive & Predictive Analysis:** Apply statistical techniques (regression, hypothesis testing, utilization analysis) to uncover trends and high-impact opportunities.
- ❑ **Data Visualization & Dashboards:** Develop interactive dashboards in Tableau and Power BI that deliver insights to leadership in real time.
- ❑ **Reporting & Insight Generation:** Convert complex analytics into concise, actionable findings that strengthen operational and patient-outcome strategies.
- ❑ **Clinical & Business Communication:** Present results clearly to clinicians, administrators, and cross-functional teams, driving adoption of data-driven decisions.

My tool set



Project 1

Malaria Risk Mapping: A Data-Driven Approach

Context

Background

- ❑ Aimed to use burden of disease for prioritization, complemented by intervention-specific indicators to maximize impact, with the purpose of reducing malaria incidence in Angola in 2021.

Skills

- ❑ Tools SQL, Excel (Power Query), and EPI-MAP

- ❑ Identify the populations and municipalities at highest risk of malaria.
- ❑ Identify the geographic areas and populations that require the most resources to reduce malaria incidence.
- ❑ Identify the essential service package according to the population's risk level.

- ❑ Data transformation and integration coming from District Health Information Software – 2 (DHIS2)
- ❑ Routine case data from all 164 municipalities of Angola (monthly, 2018–2020) covering all ages were analyzed.
- ❑ Survey prevalence, and environmental covariates from Angola (2015–2020) were combined to model malaria-attributable fevers, focusing on all ages and children under five.

Project 1

Process

Data import and preparation

- ❑ Consolidating datasets from multiple systems: DHIS2,
- ❑ 2015/16 DHS survey
- ❑ Merged the different sources of data
- ❑ Cleaning and transformation data, ensuring accuracy
- ❑ Estimated new variables: Malaria prevalence and Joint modeling of incidence and prevalence



Analysis

- ❑ Analysis of several models using visualizations, including geo maps and scatterplots.
- ❑ Statistic correlation analysis between modeled incidence and prevalence

Visualizations

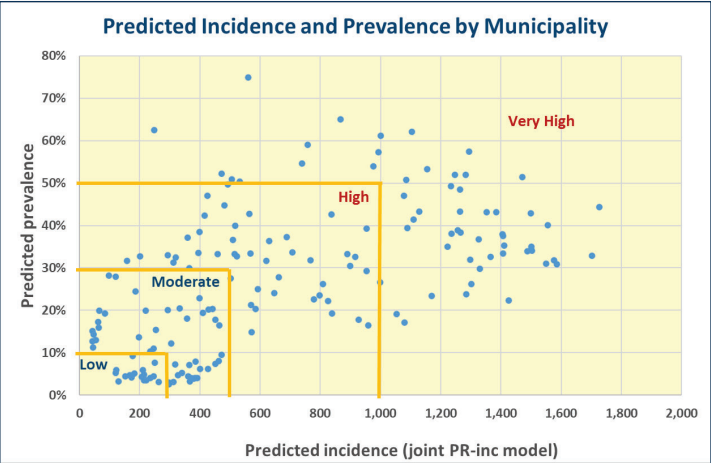
- ❑ Identification of modeled malaria risk levels through a scatterplots chart.
- ❑ Created and plotted a national risk map identifying four risk levels (very high, high, medium, and low) based on the correlation analysis of the variables.



1. Criteria for defining risk strata

Strata	Incidence	Prevalence
Low	<300	< 10%
Moderate	300 – 500	10 - 30%
High	500 – 1000	30 - 50%
Very High	> 1000	> 50%

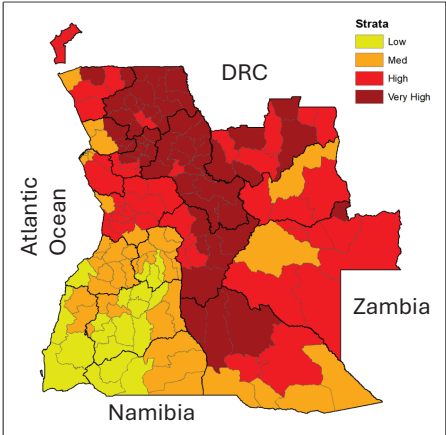
2. Identification of modeled malaria risk level



Insights

- ❑ Angola, with 32 million inhabitants, is divided into 16 provinces and 164 municipalities.
- ❑ Malaria is the country’s leading cause of illness and death, with an incidence rate of 236 cases per 1,000 people at risk in 2022.
- ❑ Using incidence and prevalence data, municipalities were classified by risk level, allowing precise identification of populations most at risk.
- ❑ By consensus, risk thresholds were identified based on predicted incidence and prevalence (scatter plot).

3. Angola – Risk Map



Breakdown of risk strata in Angola

Risk Strata	N districts	Population	% Population
Very High	55	3,9 M	12.7%
High	45	7,3 M	23.6%
Moderate	45	14,9 M	48.2%
Low	19	4,8 M	15.5%
Total	164	31.2 M	

Insights

- ❑ Stratification identified 90 districts, covering 36% of Angola’s population (11.2M), as ‘high’ or ‘very high’ risk.
- ❑ Based on these findings, the Ministry of Health defined malaria strategies: vector control, early diagnosis and treatment, surveillance and M&E, and behavior change communication.
- ❑ Due to budget constraints, comprehensive benefit packages were directed to high-risk populations, while low-risk areas received palliative packages.

Project 1

Results and Recommendations

Results

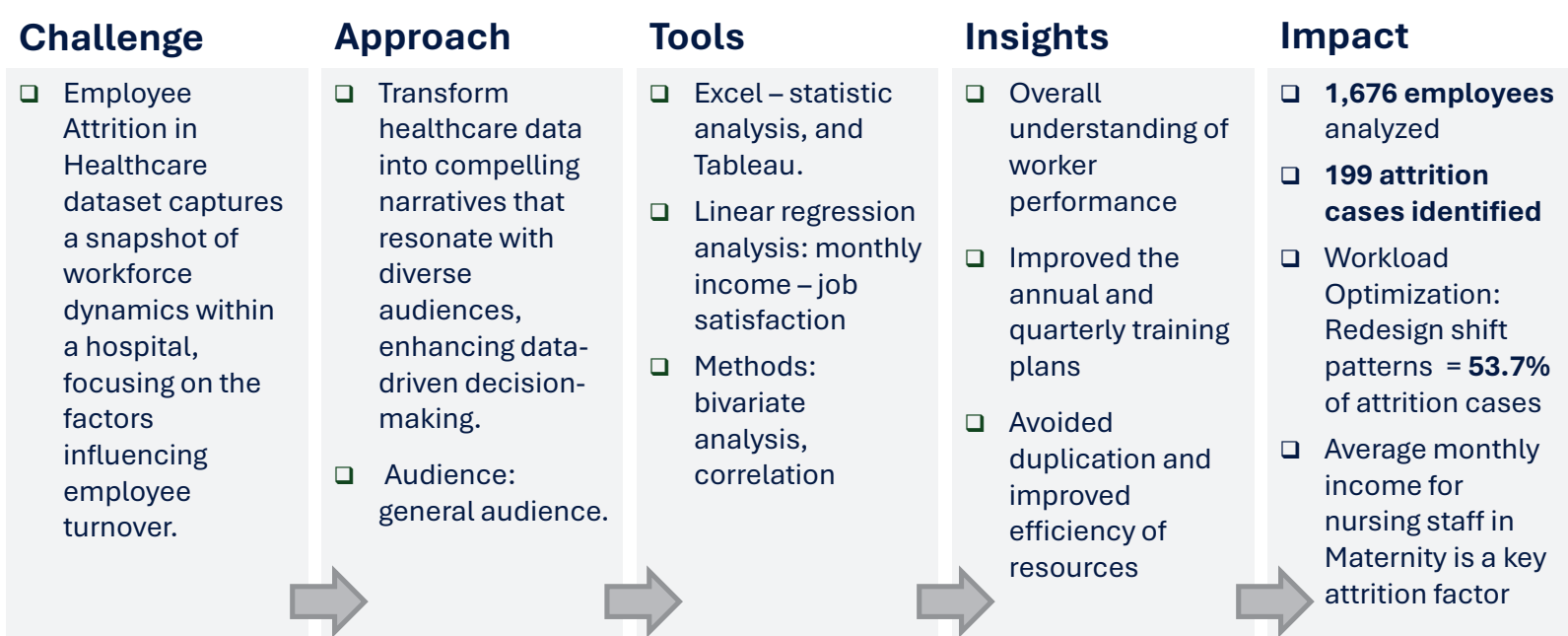
- ❑ Developed the first Malaria Risk Map in Angola (2021)
- ❑ In this hyper-endemic country, 90 districts and their populations at very high and high risk of malaria were identified
- ❑ Outlined key anti-malaria strategies to be prioritized in these high-risk areas, including the use of bed nets, early diagnosis and treatment, surveillance, and engagement of community health workers.

Recommendations

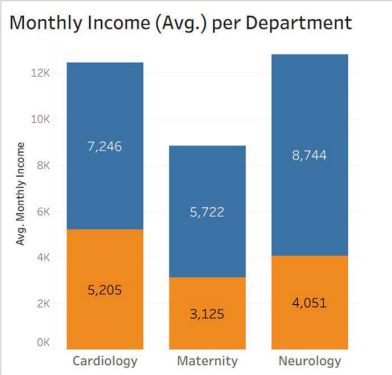
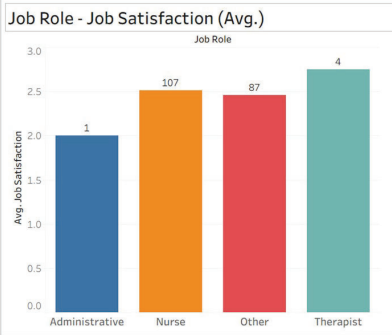
- ❑ Promote, across all institutional levels of the Ministry of Health, the preparation and delivery of epidemiological reports, ensuring data quality and timely submission.
- ❑ Strengthen the Ministry of Health's public information system (DHIS2)
- ❑ Continue applying prioritization mechanisms to identify the most cost-effective health strategies, contributing to the reduction of malaria incidence and prevalence nationwide.

Project 2

Data Storytelling Analyzing the major reasons for nurse attrition as high-risk group



Major reasons – Low job satisfaction level



- ❑ The data reveals a noticeably low level of job satisfaction among the professional and technical staff of the hospital under study; nurses are the group most likely to leave the institution (**high-risk group**).
- ❑ Within the clinical staff categorized as attrition, a segment of 167 individuals (83.9% of the total 199) are concentrated in the **Maternity** and **Cardiology Departments**
- ❑ A total of **107 nurses** (13%) out of 822 were recorded as cases of attrition.
- ❑ They also account for 53.7% of the 199 technical personnel identified as being in an attrition status.
- ❑ In the Maternity Department, dissatisfied staff members have an average monthly income of **\$3,125**, while those who report being satisfied earn an average of **\$5,722** per month (Chart 2).
- ❑ In the Cardiology Department, dissatisfied personnel earn an average of **\$5,205** monthly, whereas staff in the Neurology Department have an average income of **\$4,051**.
- ❑ This pattern may indicate that **compensation disparities** represent a key factor contributing to **nurses’ demotivation and job dissatisfaction**.

Project 2

Results and Recommendations

Implications

The **disengaged performance of healthcare personnel** within a clinical unit **may compromise the quality of care**, particularly in terms of adherence to clinical protocols and the timeliness of interventions. Based on the main findings, hospital management should consider the following:

- ❑ Compensation and Benefits
- ❑ Operational Factors and Work-Life Balance.
- ❑ Career Growth and Promotions.
- ❑ Nursing Staff Retention

Strategy recommendations

High priority (high impact)

- ❑ Workload Optimization – Redesign shift patterns
- ❑ Well-being and support programs.

Medium term (moderate cost)

- ❑ Career paths and internal promotions
- ❑ Compensation review for critical roles

Low cost

- ❑ Recognition and feedback culture
- ❑ Organizational micro-interventions in communication

Project 3

Control mechanisms for the National Health Worker Training Program

Challenge

- ❑ Weak national monitoring and evaluation system of the malaria training program implemented in **six provinces, 60 municipalities, and 942 health facilities.**

Approach

- ❑ Implementing a **monitoring and evaluation** system.
- ❑ Overall **performance** assessment of trained health workers
- ❑ **Data transformation** and integration

Tools

- ❑ Excel advanced, data entry, pivot tables, formulas, functions, pivot chart
- ❑ Visualization and reports – M&E system in quarterly basis.

Insights

- ❑ Overall understanding of worker performance
- ❑ Improved the annual and quarterly training plans
- ❑ Avoided duplication and improved efficiency of resources

Impact

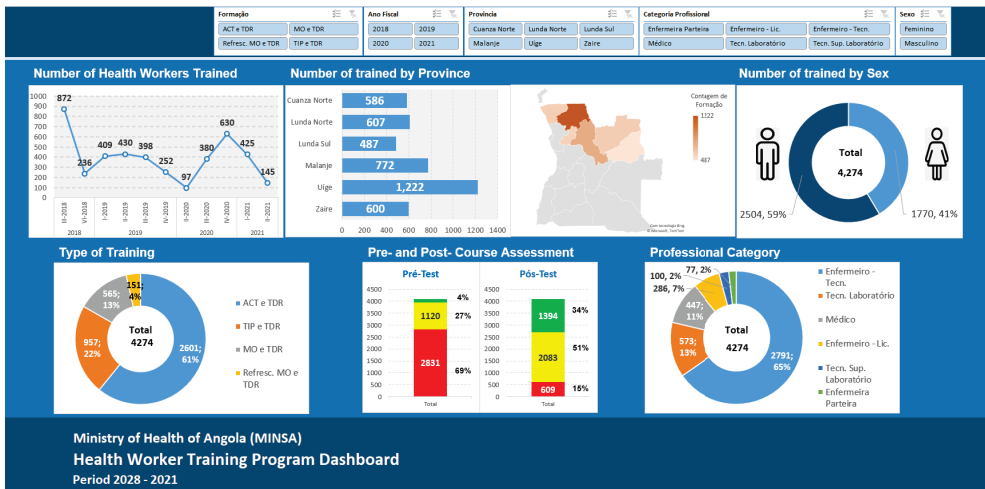
- ❑ 4,200 health workers trained
- ❑ Performance improved by 21% (grade above 80%)
- ❑ Dashboard adopted by Ministry of Health



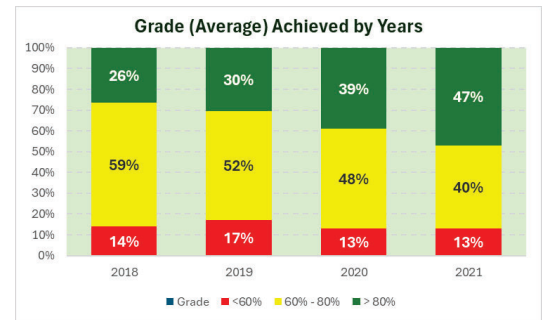
Project 3

Insights

Health Workers Training Program Dashboard



- ❑ In **2018**, the Angolan Ministry of Health (MOH) developed a **tool to monitor the malaria training program**.
- ❑ With this tool, **duplication** of training sessions was **avoided**, thereby **improving efficiency**.
- ❑ Reports disaggregated by type of training, gender, provinces, municipalities, technical category, and performance in quarterly basis.



Health workers performance

- ❑ The MOH was finally able to gain an overall understanding of worker performance, moving from qualitative assessments to quantitative results.
- ❑ Overall performance improved from **26%** in 2018 to **47%** in 2021 (grade above 80 points).

Project 3

Results and Recommendations

Results

- ❑ Health Workers Training Program Dashboard
- ❑ The Angolan MOH authorities obtained a quantitative assessment of their workers' training performance and gained insights into the cost-effectiveness of the program.
- ❑ After its adoption, the dashboard was embraced by the MOH authorities as a management tool for their program.

Recommendation

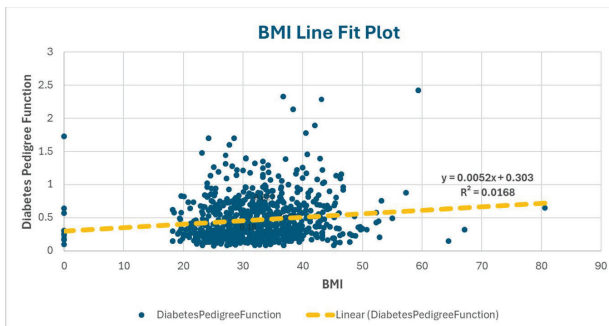
- ❑ During the period 2018–2021, **4,200 health workers** were **trained** in malaria case management.
- ❑ Encourage the timely submission of training reports.
- ❑ Continue updating the database to manage the program more efficiently.
- ❑ Use this tool to present to donor agencies and expand it nationwide.

Project 4

Relationship Between Body Mass Index (BMI) and Diabetes Pedigree Function (DPF)

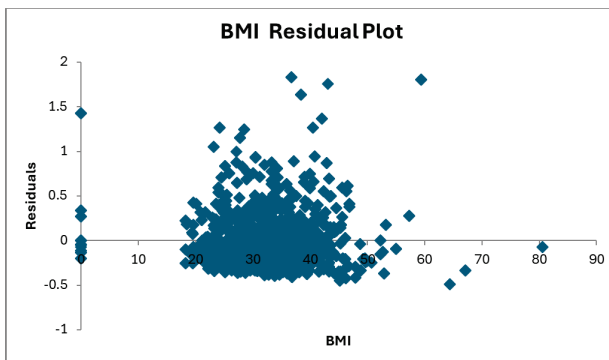
Challenge	Approach	Tools	Insights	Impact
<ul style="list-style-type: none">□ Explore the relationship between Body Mass Index (BMI) and the Diabetes Pedigree Function (DPF), which reflects a patient's hereditary likelihood of developing diabetes.	<ul style="list-style-type: none">□ Analysis diabetes dataset of 2,768 patients.□ Simple linear regression□ $DPF = \beta_0 + \beta_1(BMI)$□ β_0 (Intercept): Expected DPF when BMI = 0.□ β_1 (Slope): How much DPF is expected to change per one-unit increase in BMI.	<ul style="list-style-type: none">□ Excel statistical analysis – linear regression analysis□ Included:<ul style="list-style-type: none">□ R^2 (model fit)□ Coefficients (effect size)□ Visuals:<ul style="list-style-type: none">□ BMI Line Fit Plot□ BMI Residual Plot	<ul style="list-style-type: none">□ The relationship is statistically significant but weak (small $R^2 = 0.017$).□ BMI Line Fit Plot suggest a mild positive association between body mass and hereditary diabetes risk	<ul style="list-style-type: none">□ Confirmed linearity but highlighting limited explanatory power of BMI on DPF

Visualizing the Relationship Between BMI and DPF



BMI Line Fit Plot

- The chart shows a **slight upward trend**, indicating that patients with higher BMI values tend to have **marginally higher DPF values**, suggesting a **mild positive association** between body mass and hereditary diabetes risk.
- $Y = 0.030 + 0.0052x$



BMI Residual Plot

- Residuals show **random dispersion around zero**, confirming linearity but highlighting **limited explanatory power** of BMI on DPF.
- No visible trend. No major bias or nonlinearity.
- Moderate vertical spread \rightarrow BMI explains only a small portion of DPF variability ($R^2 \approx 0.017$).
- A few outliers for very high or low BMI values, common in medical data.

Project 4

Results and Recommendations

Results

- ❑ A simple linear regression was performed to evaluate the relationship between Body Mass Index (**BMI**) and the Diabetes Pedigree Function (**DPF**) among **2,768 patients**.
- ❑ The model was **statistically significant** ($p < 0.001$) and explained approximately **1.68%** of the **variance in DPF** ($R^2 = 0.017$).
- ❑ **BMI** was found to be a **positive predictor of DPF** ($\beta = 0.0052$, $p < 0.001$), indicating that as **BMI increases**, the expected value of the **Diabetes Pedigree Function also rises slightly**.
- ❑ While the effect size is small, this finding suggests that higher body weight may be modestly associated with greater hereditary predisposition to diabetes.

Conclusions

- ❑ The relationship is statistically significant but weak (small R^2).
- ❑ BMI alone cannot predict hereditary diabetes risk, but it may contribute when combined with other factors.
- ❑ This supports the concept of **multifactorial risk**: genetics, age, BMI, glucose, pregnancies, and insulin together explain patient outcomes better.

Education

Master of Health Economics, 2005 – 2007

Universidad Nacional Autonoma de Nicaragua (UNAN) – Managua, Nicaragua

Bachelor of Economics, 1986 - 1991

Universidad Nacional Autonoma de Nicaragua (UNAN) – Managua, Nicaragua

Certifications

0214 License – Life & Variable Contracts Insurance Agent (Active)

Florida Department of Financial Services

0240 License – Health Insurance Agent (Active)

Florida Department of Financial Services

Data Analyst in Healthcare Certificate.

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