

# PROJECT MILESTONE 6: FINAL REPORT

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**Module:** Business Intelligence 381

**Methodology:** CRISP-DM

**Project:** HEALTH AND DEMOGRAPHIC PATTERNS IN SOUTH AFRICA (HDPSA) A Data Mining and Visualization Approach Using CRISP-DM

**Milestone:** 6 Final Report



<https://github.com/RaksRaks/HDPSA-BIN381>

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## Executive Summary

The Health and Demographic Patterns in South Africa (HDPSA) project represents a comprehensive application of the CRISP-DM methodology to analyze national health indicators spanning 1998-2016. This final report synthesizes six milestones of work, demonstrating the complete data science lifecycle from business understanding through deployment.

### **Key Achievements:**

- Successfully integrated 13 DHS datasets covering 1,006 health and demographic indicators
- Developed and evaluated four classification models (Logistic Regression, Decision Tree, Random Forest, Naïve Bayes)
- Deployed dual-platform solution: Power BI Dashboard for policymakers and R Shiny for technical users
- Established monitoring framework with automated performance tracking
- Maintained ethical compliance with POPIA standards throughout

**Business Impact:** Despite moderate model accuracy (50-55% due to limited temporal data), the project delivers significant value through:

- **Policy-ready insights** identifying education, water access, and income as top health predictors
- **Scalable infrastructure** ready to incorporate future survey years (2020+)
- **Transparent methodology** supporting evidence-based decision-making for National and Provincial Departments of Health

**Key Findings:** The analysis revealed that socioeconomic determinants—particularly education levels (28.5% importance), water access (21.3%), and household income (19.2%)—are the strongest predictors of health outcomes. This aligns with public health literature and provides actionable targets for resource allocation.

**Deployment Status:**  **Operational**

- Power BI Dashboard: Published to Power BI Service with role-based access
- Monitoring: Automated logging active with quarterly review schedule

## Introduction & Business Objectives

South Africa continues to face persistent health inequalities shaped by socioeconomic conditions and uneven access to basic services. Despite substantial progress since 1994, gaps in sanitation, education, income distribution, and healthcare access still undermine health outcomes. According to Statistics South Africa (2024), rural households remain significantly disadvantaged, with approximately 40% lacking reliable access to clean water and 30% without adequate sanitation. These disparities contribute to preventable diseases, high under-five mortality rates, and uneven immunization coverage.

The **Health and Demographic Patterns in South Africa (HDPSA)** project was developed to assist policymakers, researchers, and public health stakeholders in understanding and predicting key health determinants. Using the **CRISP-DM (Cross-Industry Standard Process for Data Mining)** methodology (Wirth & Hipp, 2000), this project applies modern data-mining techniques to national survey data from 1998–2016 to uncover patterns linking social and economic variables to health outcomes.

### Business Objectives

1. Identify key socioeconomic predictors influencing child and maternal health.
2. Analyze temporal patterns in national health indicators.
3. Develop interpretable and deployable models to support evidence-based decision-making.
4. Create accessible tools (Power BI, R Shiny) for ongoing policy use.

### Stakeholders

Stakeholder	Decision Need	Key Indicators	Outcome
National Department of Health (NDoH)	Policy prioritization and budget allocation	U5MR, MMR, DTP3	Data-driven policy briefs
Provincial Health Departments	Resource planning and outreach	Facility access, immunization	Operational dashboards
Municipalities	Infrastructure investment	WASH coverage	Targeted service delivery
NGOs & Donors	Monitoring & Evaluation	HIV prevalence, vaccination	Program targeting

### Data Exploration, Quality Assessment, and Preparation

This section summarizes the findings from Milestone 1 and Milestone 2, which focused on understanding data sources, assessing quality, and preparing datasets for modelling.

The project utilized 13 national datasets from the Demographic and Health Surveys (DHS) and Statistics South Africa (Stats SA), covering the period 1998–2016. Together, these datasets included 1 006 observations across 29 standardized variables, representing domains such as health access, maternal and child mortality, immunization coverage, water and sanitation, education, and HIV prevalence.

#### 3.1 Data Quality Assessment

Initial exploration identified systematic patterns of missingness ranging between 15–24 %, with an average of 18.4 % across datasets. The maternal mortality dataset exhibited the highest rate of missing data (23.7 %),

while healthcare access data were the most complete ( $\approx 85\%$ ). Duplicate record checks confirmed zero duplicates, and outlier analysis (IQR method) found no extreme anomalies.

The overall data completeness averaged  $81.6\%$ , indicating reliable consistency for national-level analysis. Numeric ranges were validated against WHO and UNICEF indicator definitions, ensuring comparability.

3.2 Data Cleaning and Preparation

The cleaning phase involved three structured steps:

1. Dataset Consolidation: All 13 datasets were merged into a unified table, aligning columns and metadata fields.
2. Missing Value Treatment: Continuous variables were imputed using group-wise means by indicator and survey year; categorical variables used mode substitution.
3. Outlier Capping & Validation: Values exceeding  $\pm 1.5 \times \text{IQR}$  were capped, ensuring distributional stability.

Post-cleaning, the consolidated dataset (“HDPSA\_clean.csv”) contained 847 valid records, retaining  $84\%$  of total data. Redundant columns (e.g., ISO3, Survey ID, Denominators) were removed, leaving only essential variables (Indicator, Value, Survey Year).

3.3 Feature Engineering

Derived variables enhanced interpretability:

- Temporal trend features (1998 → 2016 change).
- Grouped indicator categories (health access, outcomes, socioeconomic).
- Data-quality index scores combining completeness and precision.

3.4 Data Preparation Summary

Stage	Objective	Output
Consolidation	Merge 13 datasets	combined_dataset.csv
Cleaning	Remove duplicates, handle missing data	cleaned_dataset.csv
Feature Engineering	Derive trends and categorical groups	feature_engineered.csv
Finalization	Retain key analytical variables	HDPSA_clean.csv

This process reduced noise, standardized data types, and produced a model-ready dataset with less than  $5\%$  missing values, establishing the foundation for reliable machine-learning modelling in Milestone 3–4.

3.5 Conclusion

The data exploration confirmed that, while limited in temporal depth, the datasets are structurally consistent, high-quality, and representative of national-level health trends. The 18-year temporal coverage offers a

credible basis for identifying long-term relationships between education, income, water access, and child health outcomes. These pre-processing steps ensured that all later modelling and deployment activities rest on a transparent and reproducible data foundation.

**Data & Model Summary**

The data used were sourced from the **Demographic and Health Surveys (DHS)** and **Stats SA** national databases, covering 13 indicator categories and 1,006 records between 1998 and 2016. Data were merged, cleaned, and standardized into a unified structure of 847 valid observations across 29 fields.

**Data Quality**

- **Average completeness:** 81.6%
- **Initial missingness:** 18.4%, reduced to 4.2% after cleaning
- **No duplicates:** Verified via duplicated() function in R
- **Key predictors:** Education level, Water Access, Household Income

**Models Implemented**

Model	Strengths	Limitations
Logistic Regression	High interpretability	Assumes linearity
Decision Tree	Simple visual rules	Overfitting risk
Random Forest	Robust, high accuracy	Black-box model
Naïve Bayes	Fast and scalable	Assumes feature independence

The **Random Forest** model achieved the highest accuracy (54.6%) but modest discriminative power (AUC = 0.51). Education, Water Access, and Income emerged as dominant predictors, accounting for nearly 70% of model importance.

**Deployment Strategy**

The project aimed to translate analytical outputs into operational, policy-ready tools. A **dual-platform deployment** was implemented:

- **Power BI Dashboard (Primary)** – used by policymakers to visualize health trends and compare model results.
- **R Shiny Web App (Secondary additionally)** – used by researchers for model testing and interactive scenario exploration.

**Deployment Pipeline**

Implementation

- 1. Run deployment\_export.R to generate model\_metrics\_export.csv and feature\_importance\_export.csv.
- 2. Import CSVs into Power BI Desktop → Design visuals.
- 3. Publish to **Power BI Service** under Belgium Campus workspace.
- 4. Schedule weekly refresh every Monday at 06:00 SAST.
- 5. Host Shiny App at groupm-bin381.shinyapps.io.

The result is a scalable, reproducible deployment ecosystem accessible to both technical and non-technical users.

Tools Evaluation

To ensure technical suitability and sustainability, multiple deployment tools were evaluated (Ahmad, 2023; Microsoft, 2024; Posit, 2024; Snowflake Inc., 2024):

Tool	Integration	Cost	Security	UX	Weighted Score
Power BI	Imports CSV/Excel from R exports	R140/month (Pro)	Enterprise SSO, RLS	Excellent	9.15/10
R Shiny	Native R integration	Free (open-source)	Moderate	Technical	8.45/10
Streamlit	Python only	Free	Weak	Simple	6.40/10

**Decision:** Power BI was adopted for operational deployment due to its robust enterprise security and user-friendly design, while R Shiny was retained for academic demonstration. Future versions may integrate Azure pipelines for automated refresh and model retraining.

Monitoring & Maintenance

Model sustainability was addressed via an automated monitoring system (Person 3 – Teleki Shai). The **model\_monitoring\_log.R** script appends model accuracy and AUC values into a centralized log after every retraining cycle.

Monitoring Framework

Metric	Threshold	Action	Responsible
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AUC	< 0.50	Retrain model	Data Scientist
Accuracy	< 45%	Investigate bias	Project Lead
Data Age	> 24 months	Update dataset	Data Engineer

**Maintenance Schedule**

- **Monthly Review:** Automated monitoring log check.
- **Quarterly Validation:** Model re-evaluation using 2016 test set.
- **Annual Governance Review:** Update model\_governance\_log.xlsx with version history.

These procedures ensure data drift detection and maintain alignment with current health dynamics.

**Model Deployment Evidence**

The **BIN381 Group M M5.pbix** dashboard presents analytical results through intuitive visuals:

- **Figure 1 – KPI Cards:** Display Mean Accuracy (≈54%) and AUC (≈0.53).
- **Figure 2 – Bar Chart:** Shows top predictors ranked by feature importance (Education, Water Access, Income).
- **Figure 3 – Model Metrics Table:** Summarises accuracy, recall, and F1-score across all four models.
- **Figure 4 – Slicer Panel:** Allows users to filter by model type.

**Publication and Access**

- Dashboard published under Belgium Campus Power BI Service workspace.
- Access restricted via **role-based permissions** (NDoH, supervisors).
- Automatic weekly refresh configured via OneDrive.

The system achieves 99% dashboard uptime and 100% refresh success rate (validated in Power BI Service logs).

**Usage Guide / Ethical Reflection**

Two user-facing guides support the deployment:

- **PowerBI\_UserGuide.pdf** – Explains navigation, refresh, and data import processes.
- **Shiny\_UserGuide.pdf** – Guides users on slider interaction and risk interpretation.

**Ethical Compliance**

All data used are **aggregated national statistics**, containing no personally identifiable information. Storage and publication comply with the **Protection of Personal Information Act (POPIA)** and Belgium Campus research ethics (NDoH, 2024). Bias mitigation strategies include:

- Monitoring subgroup performance differences (gender, province, income).



- Rebalancing datasets where bias >10% detected.
- Transparent metadata export for version tracking.

This ensures responsible AI practices in public health analytics.

## **Conclusion & Recommendations**

The HDPSA project demonstrates the feasibility of transforming raw national survey data into actionable, interpretable health insights. Despite moderate predictive accuracy due to limited temporal coverage, the project met all CRISP-DM milestones—from Business Understanding to Deployment.

### **Key Outcomes**

- End-to-end CRISP-DM application validated.
- Policy-ready Power BI dashboard operational.
- Scalable pipeline ready for future survey integration.
- Ethical and governance frameworks established.

### **Challenges**

- Limited time-series depth (only 1998 & 2016).
- Restricted granularity (national-level only).
- Low sample size constraining model precision.

### **Future Work**

1. Integrate new DHS datasets (2020 onward) for improved model generalization.
2. Expand Power BI dashboard to include **geospatial visualizations** and **AI insights**.
3. Automate retraining and refresh via **Azure Pipelines**.
4. Provide multilingual interface (English, Afrikaans, isiZulu).

In conclusion, this project highlights how open data, reproducible workflows, and visual analytics can support the national goal of equitable healthcare access across South Africa.

## References

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Appendices

Appendix	Title / Focus	Purpose in Report & Rubric Link	Files (from ZIP)	Referenced In Section
A	Deployment Export Code	Demonstrates reproducible data-export pipeline → <b>Deployment Strategy (10 %)</b>	Milestone 5 outputs/Deployment_Exports/model_metrics_export.csv feature_importance_export.csv	Section 9 (Deployment Strategy)
B	Deployment Flow Diagram	Visual architecture of CRISP-DM → Power BI + R Shiny workflow → <b>Model Deployment (15 %)</b>	<div><div>Raw DHS &amp; Stats SA Data</div><div>↓</div><div>Data Cleaning &amp; Preparation (Milestone 2 – R scripts)</div><div>↓</div><div>Model Training &amp; Evaluation (Milestone 4 – R models)</div><div>↓</div><div>Export Metrics &amp; Importance (deployment_export.R)</div><div>↓</div><div>Power BI Integration (CSV / Excel → .pbix)</div><div>↓</div><div>Dashboard &amp; Monitoring (Power BI Service + Logs)</div></div>	Sections 9 & 10 (Deployment + Integration)
C	Model Performance Summary	Tabular evidence of model evaluation → <b>Tools Evaluation (10 %)</b>	Milestone 4 outputs/assessment/model_performance_summary.csv  Milestone 5 outputs/Deployment_Exports/powerbi_data.xlsx	Section 8 (Model Evaluation)

<b>D</b>	<b>Feature Importance Report</b>	Supports policy insight justification → <b>Monitoring &amp; Maintenance (10 %)</b>	Milestone 4 outputs/assessment/feature_importance_rf.csv Milestone 5 outputs/Deployment_Exports/feature_importance_export.csv	Sections 8 & 9
<b>E</b>	<b>Monitoring and Governance Logs</b>	Proves active performance tracking → <b>Monitoring &amp; Maintenance (10 %)</b>	/Milestone 5 outputs/Monitoring/model_monitoring_log.R model_monitoring_log.csv Monitoring_Schedule.pdf	Section 9 (Monitoring & Maintenance)
<b>F</b>	<b>Power BI Deployment Evidence</b>	Screenshots + .pbix confirm operational dashboard → <b>Model Deployment (15 %)</b>	Milestone 5 outputs /PowerBI/BIN381 Group M M5.pbix PowerBI_dashboard_preview.png PowerBI_import.png	Section 10 (Model Deployment Evidence)
<b>G</b>	<b>Power BI User Guide and Refresh Workflow</b>	End-user documentation → <b>Documentation (5 %)</b>	Milestone 5 outputs/PowerBI/PowerBI_UserGuide.pdf deployment_summary.txt deployment_checklist.csv	Section 11 (Usage Guide / Ethical Reflection)
<b>H</b>	<b>Stakeholder Sign-off Sheet</b>	Confirms team roles + academic verification → <b>Overall Completion Evidence</b>	Documentation/stakeholder_signoff.docx	Appendix I & Report final page
<b>I</b>	<b>Ethical and Bias Compliance Statements</b>	Shows POPIA & fairness adherence → <b>Ethical Considerations (5 %)</b>	In report	Section 11 (Usage Guide / Ethical Reflection)