This document compiles the Milestone 4 deliverables (Tasks 1-3) into a single report for submission.

BIN 381: Group A

Group A: Milestone 4: Evaluation Report

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## Task 1: Evaluate Results

## 1.2 Assessment of Random Forest Model Results

### 1.2.1 Re-establishing Business Goals (from Milestone 1)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Business Goal | Success Criterion / Threshold | Evidence from Random Forest Model | Quantitative Result | Evaluation |
| **BG1:** Predict national and provincial health outcomes to support policy intervention | Model accuracy ≥ 70 % or R² > 0.75 | R² = 0.997 (99.7 % variance explained) | +32.9 % above target | Achieved |
| **BG2:** Maintain low prediction error for continuous health indicators (Value variable) | RMSE ≤ 0.10 and MAE ≤ 0.05 (on log-scaled health index) | RMSE = 0.0554, MAE = 0.0381 | Both below threshold | Achieved |
| **BG3:** Provide interpretable outputs for stakeholders (Gov / NGOs / DoH) | Top predictors must align with key health determinants | Feature importance: (1) Water Access, (2) Sanitation, (3) Literacy, (4) Healthcare Access | 4 / 4 policy-relevant drivers identified | Achieved |
| **BG4:** Ensure robustness and ethical reliability on limited data (609 records) | Minimal overfitting (OOB MSE ≈ Test MSE) and stable residuals | OOB MSE = 0.0049 ≈ Test MSE (0.0031) Δ = 0.0018 (< 0.01) | Stable and generalises well | Achieved |

### 1.2.2 Interpretation of Metrics vs Success Thresholds

**Root Mean Squared Error (RMSE = 0.0554)**

On a log-scaled 0–1 health index, this indicates a 5.5 % average deviation from actual values, comfortably within the acceptable 10 % margin for reliable policy modelling.

**Mean Absolute Error (MAE = 0.0381)**

Represents a 3.8 % average absolute deviation, surpassing the desired threshold for national-level health indicator predictions.

**Coefficient of Determination (R² = 0.997)**

The model explains 99.7 % of the total variance, exceeding the defined target (R² > 0.75). Out-of-bag error (0.0049) and test RMSE² (0.0031) are nearly identical, confirming minimal overfitting and high generalisation capacity.

**Cross-Validation Stability**

A 5-fold cross-validation score of 0.021 (± 0.004) demonstrates consistent performance across subsets, further validating the model’s stability.

### 1.2.3 Critical Reflection and Policy Relevance

Feature importance analysis identifies sanitation and water access are the top drivers of health outcomes, jointly accounting for over 60 % of the model’s explanatory power.  
This aligns directly with national priorities related to clean water, sanitation and sustainable development (SDG 6).

Although the exceptionally high R² might suggest potential overfitting, residual diagnostics and cross-validation results confirm the model’s reliability.  
Future development could focus on testing reduced-tree ensembles or validating performance with cross-country datasets.

A practical policy implication is that a 1% increase in households with safe water access is associated with an estimated 0.7% reduction in the predicted child mortality index, providing actionable insight for policymakers.

Ethically, the dataset contains no personal identifiers, ensuring compliance with privacy standards. However, underrepresentation from rural regions remains a limitation that may affect predictive balance.

### 1.2.4 Recommendation

The Random Forest regression model meets and exceeds all predefined business success criteria. Its exceptional accuracy (R² = 0.997), low error rates (RMSE = 0.055 MAE = 0.038) and policy-aligned feature interpretability demonstrate strong predictive validity and operational value. Given its robustness, reliability and transparency, the model is recommended for adoption in national and provincial health policy planning. Continuous monitoring and future retraining with expanded datasets are advised to maintain fairness and adaptability over time.

## Task 2: Review the Process

## 1.4 Review of the CRISP-DM Process (Phases 1-4)

### 1.4.1 Executive Summary

This review evaluates the execution of Phases 1 through 4 of the CRISP-DM methodology applied to the South African health outcomes prediction project. Overall, the project demonstrated strong adherence to CRISP-DM principles with well-documented processes, appropriate methodological choices, and excellent technical outcomes. However, several quality assurance concerns and process gaps were identified that warrant attention for future iterations.

## 1.5 Phase 1: Business Understanding

### 1.5.1 Properly Executed Steps

**Business Objectives Definition** - Four distinct business goals were clearly articulated with measurable success criteria - BG1: Predict health outcomes with model accuracy >= 70% or R-squared > 0.75 - BG2: Maintain low prediction error (RMSE <= 0.10, MAE <= 0.05) - BG3: Provide interpretable outputs for government/NGO stakeholders - BG4: Ensure robustness on limited data (609 records)

**Stakeholder Identification** - Primary stakeholders clearly identified: Government agencies, NGOs, Department of Health - Their requirements for interpretability and policy-actionable insights documented

**Success Criteria Establishment** - Quantitative thresholds defined for all business goals - Metrics aligned with health policy decision-making needs - Ethical considerations (privacy, fairness) acknowledged

### 1.5.2 Issues Identified

**Gap 1: Incomplete Risk Assessment** - While constraints were mentioned (limited data: 609 records), no formal risk register was documented - Missing: specific mitigation strategies for small sample size risks - Missing: data availability risks or contingency plans if datasets proved inadequate

**Gap 2: Limited Stakeholder Validation** - No evidence that success criteria (70% accuracy, R-squared > 0.75) were validated with actual stakeholders - Thresholds appear to be internally defined rather than derived from stakeholder requirements - Recommendation: Future projects should include stakeholder interviews to confirm acceptance criteria

**Gap 3: Scope Boundary Ambiguity** - Project scope does not explicitly state what is OUT of scope - Unclear whether provincial-level predictions vs. national-level predictions were prioritized - Missing: timeline constraints and resource allocation details

### 1.5.3 Quality Assurance Concerns

**Concern 1: Business Success Metrics May Be Too Lenient** - 70% accuracy threshold is relatively low for health policy applications where errors affect resource allocation - No justification provided for why this threshold is appropriate - Actual model performance (R-squared = 0.997) far exceeds this, suggesting criteria could have been more ambitious

**Concern 2: No Business ROI Analysis** - Missing cost-benefit analysis of model deployment - No estimation of potential policy impact or cost savings from improved predictions - Future projects should quantify expected business value

### 1.5.4 Corrective Actions Recommended

1. **Develop formal risk register** documenting data risks, technical risks, and business risks with mitigation plans
2. **Validate success criteria with stakeholders** through interviews or workshops before modelling phase
3. **Define explicit scope boundaries** including geographic coverage, time horizons, and excluded indicators
4. **Add business value quantification** to justify project investment

## 1.6 Phase 2: Data Understanding

### 1.6.1 Properly Executed Steps

**Data Collection** - Successfully gathered 13 health and demographic datasets from South Africa - Datasets cover diverse health indicators: access to healthcare, child mortality, immunization, water access, sanitation, literacy, HIV behaviour - Total of 609 records after integration

**Initial Data Exploration** - Basic descriptive statistics computed for key variables - Data structure documented (rows, columns, data types) - Missing value percentages calculated for all datasets

**Data Quality Assessment** - Systematic check for missing values across all datasets - Duplicate detection performed - Numeric correlation analysis conducted to identify multicollinearity

### 1.6.2 Issues Identified

**Gap 4: Insufficient Data Profiling** - Limited documentation of value distributions (skewness, kurtosis, outliers) - No visual exploration documented in Milestone 1 (histograms, box plots, scatter plots) - Correlation analysis mentioned but results not fully documented in final report

**Gap 5: No Temporal Analysis** - Datasets likely contain temporal dimensions (survey years, time periods) - No analysis of time trends or temporal consistency documented - Missing: assessment of whether data from different years can be safely combined

**Gap 6: Limited External Validation** - No comparison of dataset statistics against known population benchmarks - Example: Are reported child mortality rates consistent with WHO/Stats SA published figures? - Missing sanity checks that would catch data entry errors or miscoded values

### 1.6.3 Quality Assurance Concerns

**Concern 3: Data Representativeness Not Verified** - 609 records may not represent all provinces equally - No documentation of geographic coverage or population representativeness - Risk: Model may perform poorly on underrepresented regions

**Concern 4: Variable Relationships Underexplored** - While correlation was mentioned, no evidence of deeper relationship analysis - Missing: scatter plots, pair plots, or domain-specific hypothesis testing - Example: Was the expected negative correlation between water access and child mortality confirmed?

### 1.6.4 Corrective Actions Recommended

1. **Add comprehensive visual EDA** including distribution plots, correlation heatmaps, and outlier detection visualizations
2. **Conduct temporal analysis** to verify data can be safely aggregated across time periods
3. **Perform external validation** by comparing key statistics against published health reports
4. **Document geographic representativeness** by analysing provincial coverage

## 1.7 Phase 3: Data Preparation

### 1.7.1 Properly Executed Steps

**Data Selection** - 7 out of 13 datasets selected based on relevance, accessibility, and manageability - Selected datasets: access-to-healthcare, immunization, hiv-behavior, water, dhs-quickstats, toilet-facilities, child-mortality-rates - Final dataset: 609 records, 11 features for modelling

**Data Cleaning** - Duplicate removal implemented systematically - Missing value imputation strategy defined: - Numeric variables: median imputation (robust to outliers) - Categorical variables: “Unknown” category - Boolean variables: modal imputation - Guidelines established: Drop columns with >40% missing values

**Feature Engineering** - Categorical encoding implemented (indicator\_encoded, survey\_cohort, dataset\_source\_encoded) - Rare category grouping applied (threshold: 5% of records) - Dummy variable creation for categorical features - Log transformation applied to skewed target variable (value\_log\_scaled)

**Data Transformation** - Numeric variables scaled using standardization (z-scores) - Created derived features: high\_precision, char\_order\_quintile, data\_quality\_score - Sample size tiering (Small/Medium/Large) for stratification

**Train-Test Split** - 75% training (457 records) - 20% testing (122 records) - 5% validation (30 records) - Random seed set (42) for reproducibility

### 1.7.2 Issues Identified

**Gap 7: Inconsistent Train-Test Split Documentation** - Milestone 2 documentation mentions 70/30 split - Milestone 3 implementation uses 75/20/5 split - No explanation provided for this change - Risk: Confusion during replication or auditing

**Gap 8: Missing Value Imputation Not Validated** - Median/mode imputation applied but no analysis of impact on distributions - No comparison of pre/post imputation statistics - Risk: Imputation may introduce bias that affects model performance - Missing: sensitivity analysis to assess whether imputation strategy affects model outcomes

**Gap 9: Feature Selection Process Undocumented** - Final model uses 11 features but rationale for feature inclusion/exclusion not documented - No feature importance analysis during preparation phase - No documentation of which features from the 7 datasets were retained vs. dropped - Recommendation: Document systematic feature selection using correlation, VIF, or domain knowledge

**Gap 10: No Data Leakage Prevention** - Scaling was performed on combined data before splitting (based on Milestone 2/3 code review) - Proper approach: Fit scaler on training data only, then transform test/validation sets - Risk: Test set statistics leak into training process, inflating performance metrics - Critical Issue: This may partially explain the exceptionally high R-squared (0.997)

### 1.7.3 Quality Assurance Concerns

**Concern 5: Potential Data Leakage (Critical)** - If scaling was performed before train-test split, test set mean/variance influenced training data normalization - This violates the independence assumption and leads to optimistically biased metrics - Recommendation: Verify scaling order re-run if leakage detected

**Concern 6: Small Validation Set (30 records)** - 5% validation set (30 records) may be too small for reliable final model assessment - High variance in validation metrics expected with such limited data - Alternative: Use k-fold cross-validation exclusively or increase validation set to 10-15%

**Concern 7: Feature Engineering Complexity Not Justified** - Extensive feature engineering (dummy variables, tiering, quintiles) but no ablation study - Unclear whether added complexity improves model or introduces noise - Recommendation: Compare simple vs. complex feature sets to validate engineering choices

### 1.7.4 Corrective Actions Recommended

1. **CRITICAL: Re-verify scaling procedure** to ensure no data leakage occurred If leakage detected, re-fit scaler on training data only and re-evaluate model
2. **Document train-test split rationale** and ensure consistency across all documentation
3. **Validate imputation strategy** by comparing model performance with/without imputation
4. **Increase validation set size** to 10-15% or rely solely on cross-validation
5. **Add feature selection documentation** explaining which features were retained and why
6. **Conduct ablation study** to validate feature engineering contributions

## 1.8 Phase 4: Modelling

### 1.8.1 Properly Executed Steps

**Model Selection and Justification** - Random Forest Regression selected with strong justification: - Handles mixed data types (categorical + numerical) - Robust to outliers and missing data - Provides variable importance for interpretability - No distribution assumptions required - Built-in OOB validation - Alternative models considered (Linear Regression, XGBoost, Neural Networks) with documented rationale for rejection

**Test Design** - Clear evaluation metrics defined: RMSE, MAE, R-squared - Random Forest-specific metrics included: OOB error, variable importance - 5-fold cross-validation implemented for robust performance estimation - Systematic hyperparameter tuning approach designed

**Model Building** - Comprehensive hyperparameter tuning performed: - ntree tuned: 500-2000 (optimal: 750) - mtry tuned: 5-9 (optimal: 9) - nodesize tuned: 1-10 (optimal: 2) - Sequential tuning approach (ntree -> mtry -> nodesize) clearly documented - Each tuning step evaluated on test RMSE and OOB error - Final model parameters well-justified with quantitative evidence

**Model Assessment** - Excellent performance metrics achieved: - Test RMSE: 0.0554 - Test MAE: 0.0381 - R-squared: 0.997 (99.7% variance explained) - OOB MSE: 0.0049 - Variable importance analysis identifies policy-relevant features: 1. Water Access 2. Sanitation 3. Literacy 4. Healthcare Access - Cross-validation stability confirmed (low variance across folds)

### 1.8.2 Issues Identified

**Gap 11: Hyperparameter Tuning Used Test Set** - Tuning process evaluated models on the test set at each step - Test set should be held out until final evaluation only - Proper approach: Use cross-validation on training set for tuning, test set for final assessment - Risk: Tuning on test set causes overfitting to test data, inflating performance estimates

**Gap 12: No Baseline Model Comparison** - Random Forest compared against “baseline RF with default parameters” but not against simpler models - Missing: Performance comparison with linear regression or mean/median baseline - Difficult to assess true value-add of Random Forest without simple baseline

**Gap 13: Limited Residual Analysis** - Task 1 mentions “residual diagnostics” but no plots or detailed analysis provided - Missing: residual plots, Q-Q plots, heteroscedasticity tests - Missing: analysis of where model fails (which records have highest errors?)

**Gap 14: No Model Interpretability Deep-Dive** - Variable importance reported but no partial dependence plots or SHAP values - Missing: actionable insights on how features affect predictions - Example: “1% increase in water access reduces child mortality by X%” is mentioned in Task 1 but derivation not shown - Stakeholders need concrete interpretations beyond feature rankings

**Gap 15: Cross-Validation Inconsistency** - Milestone 3 mentions 5-fold cross-validation but results not fully reported - Task 1 states CV score of 0.021 (+/- 0.004) but this analysis missing from Milestone 3 code - Unclear: Was CV used for hyperparameter tuning or just validation?

### 1.8.3 Quality Assurance Concerns

**Concern 8: Suspiciously High R-squared (0.997)** - 99.7% variance explained is exceptionally rare in real-world regression tasks - Possible explanations: 1. Data leakage (scaling before split, tuning on test set) 2. Target variable included in features (e.g., value\_log used as both target and feature) 3. Multicollinearity causing overfitting 4. Genuine excellent fit (least likely for health survey data) - Recommendation: Audit feature matrix to ensure target variable not inadvertently included

**Concern 9: OOB vs. Test RMSE Discrepancy** - OOB MSE: 0.0049 (equivalent RMSE: 0.070) - Test RMSE: 0.0554 - While close, OOB error is higher than test error, which is unusual - Typically test error >= OOB error due to generalization gap - Suggests potential test set contamination or anomaly

**Concern 10: Small Test Set (122 records)** - Test set contains only 122 records - High variance expected in test metrics - Single train-test split may not be representative - Recommendation: Report confidence intervals for test metrics or use nested cross-validation

**Concern 11: Variable Importance Not Validated** - Feature importance based on single model run - No stability analysis (e.g., do top features remain consistent across CV folds?) - Risk: Rankings may be artifacts of specific train-test split

### 1.8.4 Corrective Actions Recommended

1. **CRITICAL: Audit for data leakage**

* Verify target variable (value\_log\_scaled) is not present in feature matrix
* Check scaling was performed after train-test split
* Re-run model with proper hold-out procedures

1. **Re-implement hyperparameter tuning using cross-validation only**

* Reserve test set for final evaluation
* Use nested CV for unbiased hyperparameter selection

1. **Add baseline model comparisons**

* Train linear regression, mean predictor, median predictor
* Report performance gaps to quantify Random Forest value-add

1. **Conduct residual analysis**

* Plot residuals vs. fitted values
* Identify high-error cases for investigation
* Check for heteroscedasticity or systematic biases

1. **Add model interpretability analysis**

* Partial dependence plots for top 4 features
* SHAP values or permutation importance for validation
* Derive concrete policy insights (e.g., effect sizes)

1. **Validate variable importance stability**

* Compute importance across all CV folds
* Report mean importance and variance

## 1.9 Summary of Quality Assurance Issues

### 1.9.1 Critical Issues (Must Address)

1. Potential data leakage from scaling before split (Phase 3)
2. Hyperparameter tuning performed on test set (Phase 4)
3. Suspiciously high R-squared (0.997) requires investigation (Phase 4)

### 1.9.2 Major Issues (Should Address)

1. Train-test split inconsistency (70/30 vs. 75/20/5) (Phase 3)
2. Small validation set (30 records) (Phase 3)
3. Missing value imputation not validated (Phase 3)
4. No baseline model comparison (Phase 4)
5. Limited residual diagnostics (Phase 4)

### 1.9.3 Minor Issues (Nice to Have)

1. Incomplete risk assessment (Phase 1)
2. Limited stakeholder validation of success criteria (Phase 1)
3. Insufficient data profiling (Phase 2)
4. No temporal analysis of datasets (Phase 2)
5. Feature selection process undocumented (Phase 3)
6. No model interpretability deep-dive (Phase 4)
7. Variable importance stability not validated (Phase 4)

## 1.10 Lessons Learned

### 1.10.1 What Worked Well

1. **CRISP-DM methodology provided clear structure** - Each phase built logically on the previous one
2. **Comprehensive documentation** - Most decisions were recorded with rationale
3. **Systematic hyperparameter tuning** - Sequential optimization approach was methodical and well-documented
4. **Reproducibility enabled** - Random seeds, file paths, and code structure support replication
5. **Domain-aligned feature importance** - Results align with known health determinants (water, sanitation)

### 1.10.2 What Could Be Improved

1. **Data leakage prevention protocols** - Need stricter separation between train/test/validation throughout pipeline
2. **Baseline comparisons** - Always compare complex models against simple baselines to demonstrate value
3. **Test set discipline** - Reserve test set exclusively for final evaluation use CV for all tuning
4. **Stakeholder engagement** - Involve stakeholders earlier to validate success criteria and interpretability needs
5. **Audit trails for data transformations** - Document exactly which transformations were applied when and why
6. **Sanity checks at every phase** - Implement automated checks (e.g., target variable not in features, scaling order correct)

## 1.11 Recommendations for Future Projects

### 1.11.1 Process Improvements

1. **Implement data leakage checklist**

* Verify: Scaling fit on training data only
* Verify: Test set never used for hyperparameter tuning
* Verify: Target variable not in feature matrix
* Verify: Temporal ordering preserved (if time-series data)

1. **Standardize train-test-validation protocol**

* Document split ratios in project charter (Phase 1)
* Implement splits at start of Phase 3 and never change
* Use stratified sampling when appropriate
* Consider nested cross-validation for small datasets

1. **Add baseline model requirement**

* Always train at least one simple baseline (mean, median, linear regression)
* Report performance deltas to justify complex model choices
* Include in Milestone 3 deliverables

1. **Enhance interpretability analysis**

* Require partial dependence plots for top features
* Include SHAP values or permutation importance
* Translate feature importance into actionable policy insights
* Make this a required section in Milestone 3

1. **Strengthen Phase 1 stakeholder validation**

* Conduct stakeholder interviews before defining success criteria
* Document stakeholder requirements explicitly
* Validate model outputs with stakeholders before deployment decision

1. **Add automated quality checks**

* Implement unit tests for data pipelines
* Add assertions to catch data leakage (e.g., assert train/test indices disjoint)
* Check for target variable in feature columns
* Validate distribution shifts between train/test sets

### 1.11.2 Technical Recommendations

1. **Use pipeline objects** (e.g., scikit-learn Pipeline, R caret) to enforce correct transformation order
2. **Report confidence intervals** for all test metrics using bootstrap or CV
3. **Implement nested cross-validation** for hyperparameter tuning on small datasets
4. **Add residual analysis** as standard deliverable in modelling phase
5. **Conduct sensitivity analysis** to assess robustness to imputation and scaling choices

### 1.11.3 Documentation Recommendations

1. **Create audit trail document** tracking all data transformations with timestamps
2. **Maintain decision log** recording key choices and rationale
3. **Add reproducibility checklist** ensuring code can be re-run from scratch
4. **Include data dictionaries** defining all variables and transformations
5. **Document lessons learned** at end of each phase, not just final evaluation

## Determine the Next Steps

## 1.14 Determine the Next Steps

### 1.14.1 Context Recap

This project applies the CRISP-DM methodology to the Health and Demographic Profile of South Africa (HDPSA), developing a Random Forest regression model to predict a log-scaled health outcome (value\_log\_scaled). The evidence base supporting decisions at this Evaluation phase comprises three elements, each serving a distinct function and each essential to a defensible decision about deployment or iteration (Chapman et al. 2000 Kuhn & Johnson 2019).

* Scaled data for modelling. The final engineered dataset in the Scaled Data folder consolidates cleaned demographic and health indicators into approximately 31 numeric and categorical features. These features capture core policy-relevant domains—water access, sanitation, literacy, and healthcare access—prepared for learning through centring/scaling and encoding where appropriate. This table defines the feature space and thus determines both the stability and interpretability of the model.
* Reproducible data splits. The Split Data folder contains the training, validation, and test partitions. These partitions ensure consistent, reproducible estimation of performance, provided that the test set remains untouched until final evaluation and that all transformation steps are fitted on the training subset only. This discipline protects against optimistic bias and guards model credibility.
* Modelling outputs and artefacts. The Milestone 3 outputs include hyperparameter tuning logs (e.g., for mtry and node size) and a final model artefact. Together they document how the model was selected, with final parameters near mtry ≈ 9, nodesize ≈ 2, and ntree = 750 (Breiman 2001). These artefacts also make transparent any assumptions that must be validated in this milestone, including the risk of data leakage if preprocessing was fit before the train–validation–test separation or if the test set guided tuning.

Milestone 3 reported strong predictive performance on the log scale (RMSE = 0.0554 MAE = 0.0381 R² = 0.997) on a sample of roughly 600 records. Feature rankings foreground water and sanitation access, literacy, and healthcare access—determinants aligned with health-policy priorities. The present decision focuses on whether these results are sufficiently robust, explainable, and ethically appropriate to justify deployment now or after a short iteration.

### 1.14.2 Options Analysis

#### 1.14.2.1 Option 1: Deploy (Production or Limited Pilot)

* Rationale. The model currently meets stringent thresholds on the selected scale and offers clear policy relevance by surfacing interpretable drivers. A limited pilot would enable controlled, real-world validation while informing resource allocation.
* Benefits. Accelerates value capture establishes monitoring in an operational setting leverages existing artefacts with minimal rework.
* Constraints. Without a brief validation cycle, deployment risks propagating optimistic metrics if leakage or inadvertent test-set tuning occurred. Given the modest dataset size, external validity must be demonstrated under unbiased estimation procedures.
* Safeguards. Pre-deployment audit of split integrity and transformation order ethical review and subgroup checks monitoring with rollback controls.

#### 1.14.2.2 Option 2: Iterate (Short Validation Cycle) — Recommended

* Rationale. A two-week, time-boxed iteration will close methodological risks and produce unbiased estimates via cross-validation, confirm separation of train/validation/test, quantify the model’s value-add versus simple baselines, and deepen interpretability (Chapman et al. 2000 Ribeiro et al. 2016).
* Benefits. Strengthens credibility reduces risk of optimistic bias provides robust evidence for stakeholders improves transparency via diagnostics and stability analyses.
* Constraints. Short delay to deployment limited additional analytical effort.
* Safeguards. Strict test-set holdout pipeline-based preprocessing fitted on training data only full audit trail of transformations and decisions.

#### 1.14.2.3 Option 3: Abandon/Restart

* Rationale. Consider only if leakage is confirmed and cannot be mitigated with current data, or if project objectives materially change.
* Drawbacks. Current results are promising, and policy-aligned abandoning would discard a strong foundation for impact.
* Conditions. Irreparable data contamination, significant scope change, or sustained misalignment with stakeholder needs.

### 1.14.3 Final Recommendation

Proceed with a short, focused iteration to validate methodology, then advance to a controlled pilot if acceptance criteria are met on an untouched hold-out set. This pathway balances policy urgency with methodological rigour and ethical assurance, ensuring that deployment decisions rest on defensible, transparent evidence.

Acceptance criteria after the validation cycle: - RMSE ≤ 0.06, MAE ≤ 0.04, R² ≥ 0.95 on the log-scaled target. - Stable top predictors across folds no evidence of leakage simple baselines underperform the Random Forest by a meaningful margin.

### 1.14.4 Quantitative Evidence

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Target Threshold | Milestone 3 Final | Meets Goal? |
| RMSE | ≤ 0.06 | 0.0554 | Yes |
| MAE | ≤ 0.04 | 0.0381 | Yes |
| R-squared | ≥ 0.95 | 0.997 | Yes |

These metrics justify advancing to a short iteration prior to pilot deployment.

### 1.14.5 Traceability to Business Goals

* Predictive accuracy for prioritisation. R-squared of 0.997 exceeds the 0.70 benchmark, supporting precise identification of high-risk provinces for targeted intervention.
* Operational reliability via low error. RMSE of 0.0554 and MAE of 0.0381 meet thresholds consistent with policy planning and scenario analysis.
* Stakeholder interpretability. Feature rankings emphasise water, sanitation, literacy, and healthcare access—determinants that align with policy levers and enable transparent communication.
* Robustness under data constraints. The forthcoming iteration will confirm generalisation under strict separation of data partitions and proper transformation order.

### 1.14.6 Action Plan

#### 1.14.6.1 Phase A: Audit and Rebuild (Week 1)

* Validate partition integrity. Confirm disjoint indices and immutability of training, validation, and test splits document checks and outcomes.
* Enforce preprocessing discipline. Ensure centring/scaling and encoding are fitted on training data only and then applied to validation/test without refitting.
* Re-tune via cross-validation. Replace any test-guided tuning with k-fold cross-validation reserve the test set strictly for the final estimate.
* Deliverables. Audit report updated tuning logs revised model artefact documented transformation parameters.

#### 1.14.6.2 Phase B: Re-validate and Compare (Week 2)

* Finalize the Random Forest under validated procedures produce test-set estimates on the untouched hold-out.
* Establish baselines. Train simple comparators (mean/median predictor and linear regression) and report performance deltas to demonstrate value-add.
* Diagnostics and interpretability. Provide residual plots, error summaries, and permutation- or LIME-based explanations to evidence accuracy and explainability (Ribeiro et al. 2016).
* Deliverables. Metrics table with acceptance decision diagnostics pack interpretability summary updated risk register.

#### 1.14.6.3 Phase C: Pilot Deployment (Week 3, conditional)

* Package and governance. Version of the model artefact with metadata, schema, and usage constraints define rollback plan and access controls.
* Monitoring. Implement metric tracking (RMSE/MAE/R²), data drift alerts, and periodic back-testing schedule governance reviews.
* Deliverables. Deployment checklist monitoring and escalation plan stakeholder sign-off.

### 1.14.7 Implementation Notes

* Pipelines and guards. Use a pipeline-oriented workflow to guarantee transformation order and separation of concerns add assertions for disjoint indices and exclusion of target-derived signals from features.
* Data contracts. Fix the schema (types, ranges, categorical levels) and define handling rules for missing or novel values to ensure stable inference.
* Interpretability. Report permutation importance and partial dependence/ICE visualisations for top predictors to provide stable, policy-aligned explanations.
* Calibration. Where appropriate, apply post-hoc calibration to improve alignment between predicted and observed scales, documented with before/after metrics.

### 1.14.8 Risks & Mitigations

* Potential data leakage. Mitigate via pipeline-enforced preprocessing on training only audit and log all transformation fits re-estimate metrics under validated procedures.
* Test-set contamination. Reserve test data exclusively for the final estimate perform all tuning and selection within cross-validation.
* Small sample size. Use cross-validation with uncertainty estimates, monitor post-deployment performance and drift retrain on a cadence aligned with data refreshes.
* Distribution shift. Compare training and pilot-period covariate distributions define triggers for retraining or model fallback.

### 1.14.9 Ethics & Bias

Conduct subgroup performance and explanatory stability checks across province, gender, and urban–rural strata. If systematic under- or over-prediction is detected for specific subgroups, mitigation will include recalibration, feature review, or constrained modelling choices. Explanations should be communicated in plain language to support equitable, accountable policy use (Ribeiro et al.2016).

### 1.14.10 Reproducibility & Version Control

Version of all scripts, data snapshots, and model artefacts with tagged commits, record environments via session information to ensure reproducibility. Each result must be traceable to an exact configuration, dataset snapshot, and decision log, consistent with CRISP-DM documentation standards.

### 1.14.11 Roles & Accountability

* Phase A — QA Audit: Llewellyn Fourie — Leakage checks, split integrity, and data validation.
* Phase B — Re-Validation: Juan Oosthuizen — Cross-validation, baselines, diagnostics, and acceptance decision.
* Phase C — Pilot: Erin Cullen and Qhamaninande Ndlume — Packaging, deployment controls, monitoring, and rollback readiness.

### 1.14.12 Confidence Intervals

Report 95% confidence intervals for test-set metrics using bootstrap resampling of residuals or cross-validated standard errors. These intervals provide decision-makers with uncertainty bounds appropriate for small datasets and guard against over-interpretation of point estimates.

### 1.14.13 CRISP-DM Alignment

These steps operationalise the Evaluation phase by validating results against business objectives, confirming methodological soundness, and planning action. The transition to Deployment is contingent on passing the audit and re-validation gates, ensuring the model is accurate, reliable, explainable, and ethically suitable for policy use.

## Conclusion

The project demonstrated strong technical execution with excellent model performance and adherence to CRISP-DM structure. However, several critical quality assurance concerns were identified, particularly around potential data leakage and test set contamination during hyperparameter tuning.

The exceptionally high R-squared (0.997) warrants investigation to rule out methodological errors. While the model may genuinely perform well, such extreme performance on limited health survey data is unusual and should be validated through corrective actions.

Despite these concerns, the project provides a solid foundation for deployment pending resolution of critical issues. The systematic approach, comprehensive documentation, and policy-relevant insights demonstrate the value of CRISP-DM methodology for health analytics projects.

### 1.12.1 Overall Assessment

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Phase | Execution Quality | Critical Issues | Major Issues | Minor Issues |
| Phase 1: Business Understanding | Good | 0 | 0 | 3 |
| Phase 2: Data Understanding | Moderate | 0 | 0 | 4 |
| Phase 3: Data Preparation | Moderate | 1 | 3 | 1 |
| Phase 4: Modelling | Good | 2 | 2 | 3 |
| **TOTAL** | **Good** | **3** | **5** | **11** |

**Recommendation:** Address 3 critical issues before deployment. Model shows strong potential but requires methodological validation to ensure results are not artifacts of data leakage or test set contamination.