Application of AI and ML in quantification of FP commodities in Kenya

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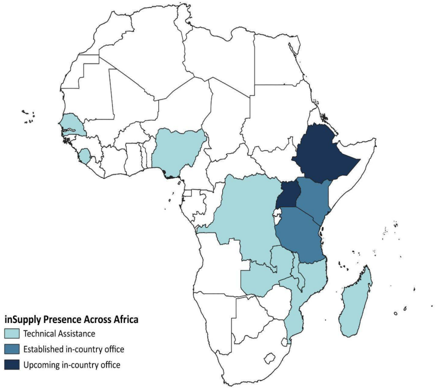
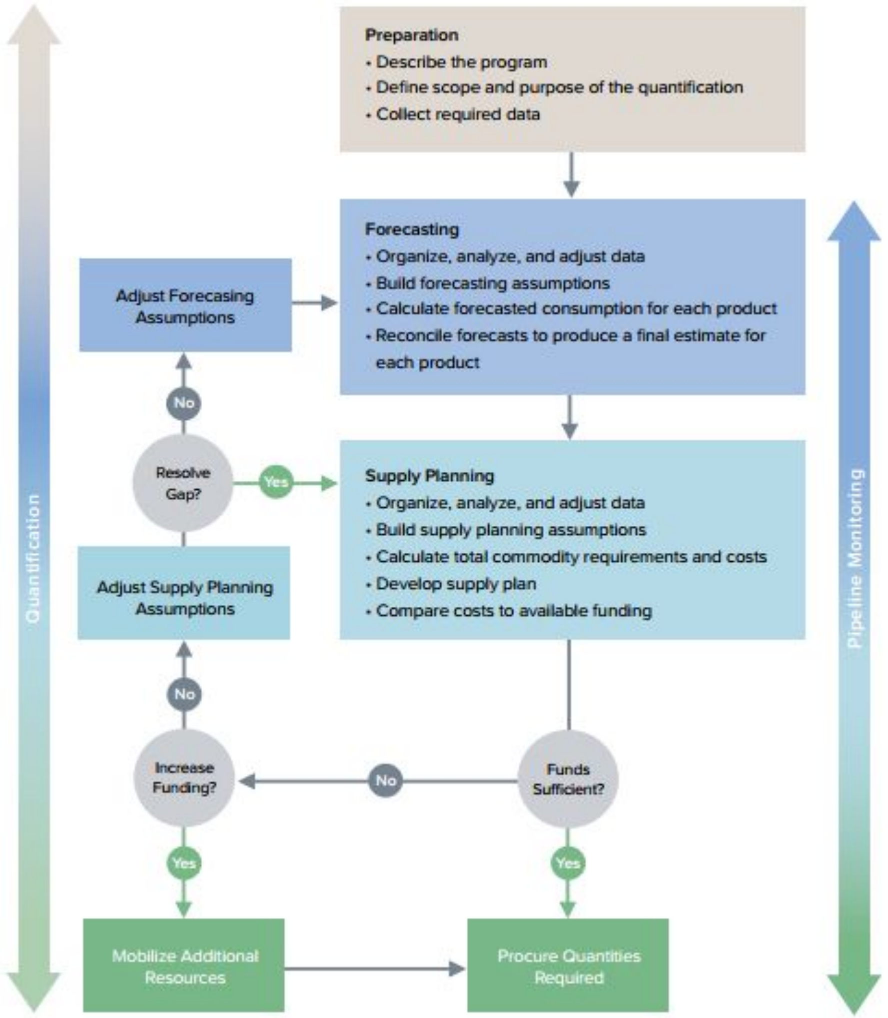
Who We Are inSupply Health, an East African health advisory firm, pioneers innovative approaches for improving equitable health access and outcomes through resilient, people-centered health systems and supply chains.

Our Mission Transforming health outcomes by co-creating intelligent and resilient people-centered supply chains.



How We Work We use human centered design and adaptive learning to articulate problems and co-create and evolve solutions with users, looking at scalability and sustainability from the start. We use a catalytic implementation model to demonstrate the impact of innovations, packaging them for adaptation in new contexts



Forecasting & Supply Planning

These are the standard, accepted steps in quantification (forecasting and supply planning) undertaken by public health programs for the vast majority of essential medicines for a robust process.

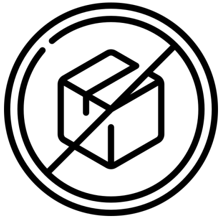
Why It's Challenging in Practice

Despite being well-established, consistent implementation remains difficult due to:

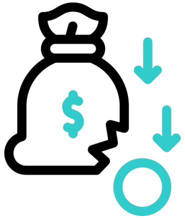
- **Fragmented and manual data sources** (consumption/logistics & service)
- **Varied forecasting methodologies** used across programs and levels
- **Time-intensive processes** that slow decision-making and responsiveness
- **Gaps between forecasted needs and available funding**, requiring iterative prioritization

Why Manual Forecasting Undermines Supply Chain Goals & Commodity Availability

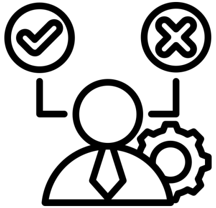
Accurate, timely forecasting is the backbone of resilient health supply chains. Without it, countries fail to ensure sufficient supplies or over-invest in inventory, leading to stockouts, expiries and wastage



Commodity Insecurity: Inaccurate planning leads to recurrent stock-outs, directly denying clients access to FP methods



Time & Resource Drain: Data preparation can take days and weeks, diverting MOH staff from strategic tasks.



Error-Prone Decisions: Manual aggregation obscures sub national disparities, masking data and needs for the **last mile** and underserved communities.

The "Days-Long" Process: Manual FP Forecasting in Kenya

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Before 2023, FP quantification was was a **labor-intensive, fragmented, and Excel based** exercise, driven by three independent teams (Consumption, Service, Demographic).

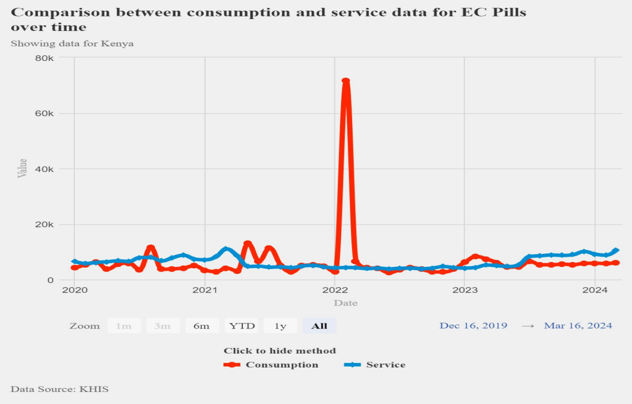
The Core Inefficiency:

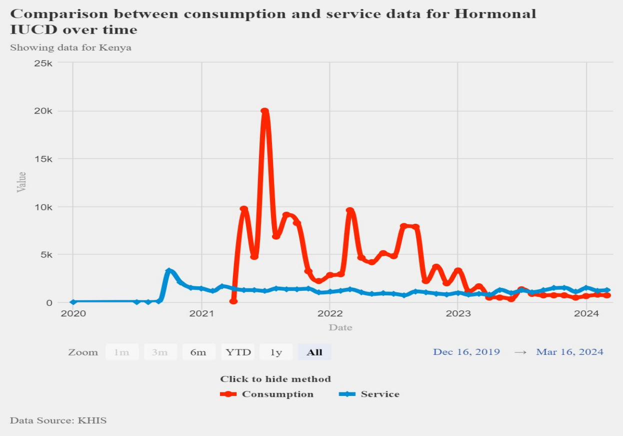
- **Time Sink: Manually extracting, cleaning and validating 1 year** of data for 13 FP products and 47 counties took an estimated **2–3 full working days** per team, leading to slow, reactive planning
- **Method Limitation:** Demand was projected using a static **Average Monthly Consumption (AMC)** multiplied by 12, which failed to account for seasonality, trends, or stockouts.
- **High Risk:** The process was highly prone to **human error** and **data inconsistency**

The Intervention

- To address this, the Ministry of Health (MOH), in partnership with inSupply Health and others, introduced Artificial Intelligence (AI) and Machine Learning (ML) into the national FP forecasting process.
- The goal was to improve accuracy, speed, and reliability through automated, data-driven methods and tools.

Original problem we set out to address: Data quality, processing and management pose the biggest barriers to forecasting principles of using multiple sources of data and methodologies since they are rely heavily on manual processes





Our Process and Approach

Identify Needs

- Map pain points in existing processes.
- Align on goals with Ministries of Health

Co-create with Users

- Workshops with planners, facility staff, and partners
- Define features and workflows together

Build, Test & Validate

- Pilot developed tools
- Validate outputs with expert insights and local context

Iterate & Improve

- Refine models based on user feedback
- Adjust for data quality and contextual realities

Scale & Handover to MOH

- Expand geographic reach
- Transfer ownership to Ministries of Health for long-term sustainability

Equity considerations are embedded in tools

The analysis uses over three years of disaggregated facility-level data, allowing better targeting of underserved populations.

The tool uses a five step process to extract data, visualize trends, detect and handle anomalies, and generate forecasts

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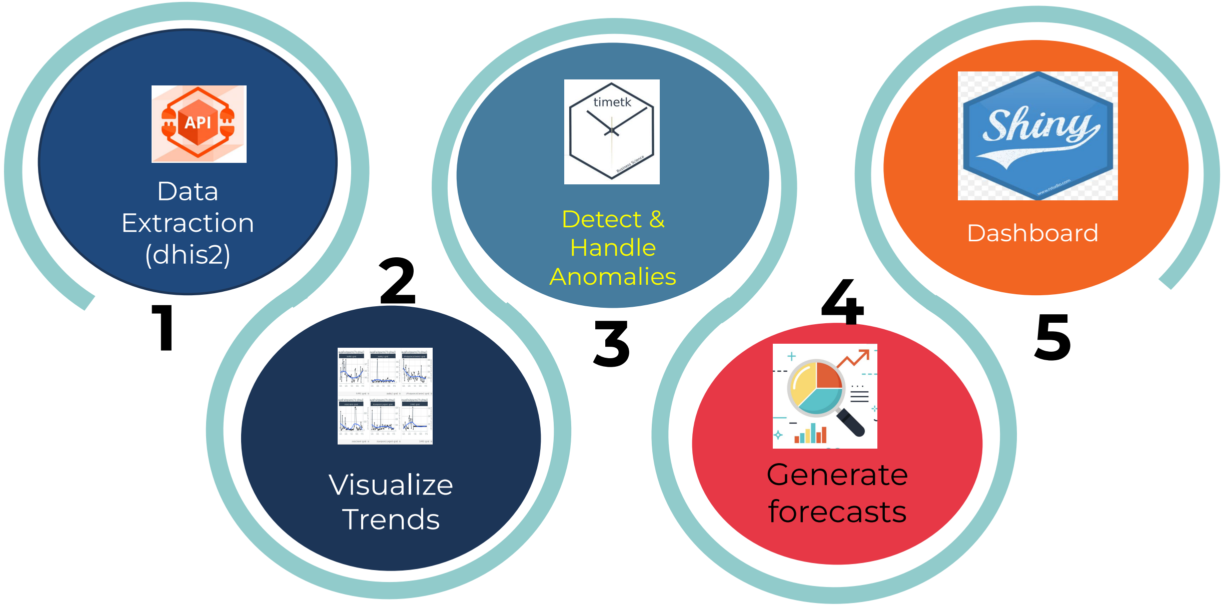
The tool uses historical family planning data and tests multiple forecasting models (e.g., XGBoost, Random Forest, and Prophet) to identify which predicts future demand most accurately.
The best model is then refitted on all available data to generate national-level forecasts for upcoming months.



The modeling process combines statistical and machine learning techniques, automatically testing and comparing different time series models to select the most accurate one. It then refines this model using the full dataset to produce reliable, data-driven forecasts for future family planning needs.

Automated data extraction and cleaning significantly increased data available for forecasting

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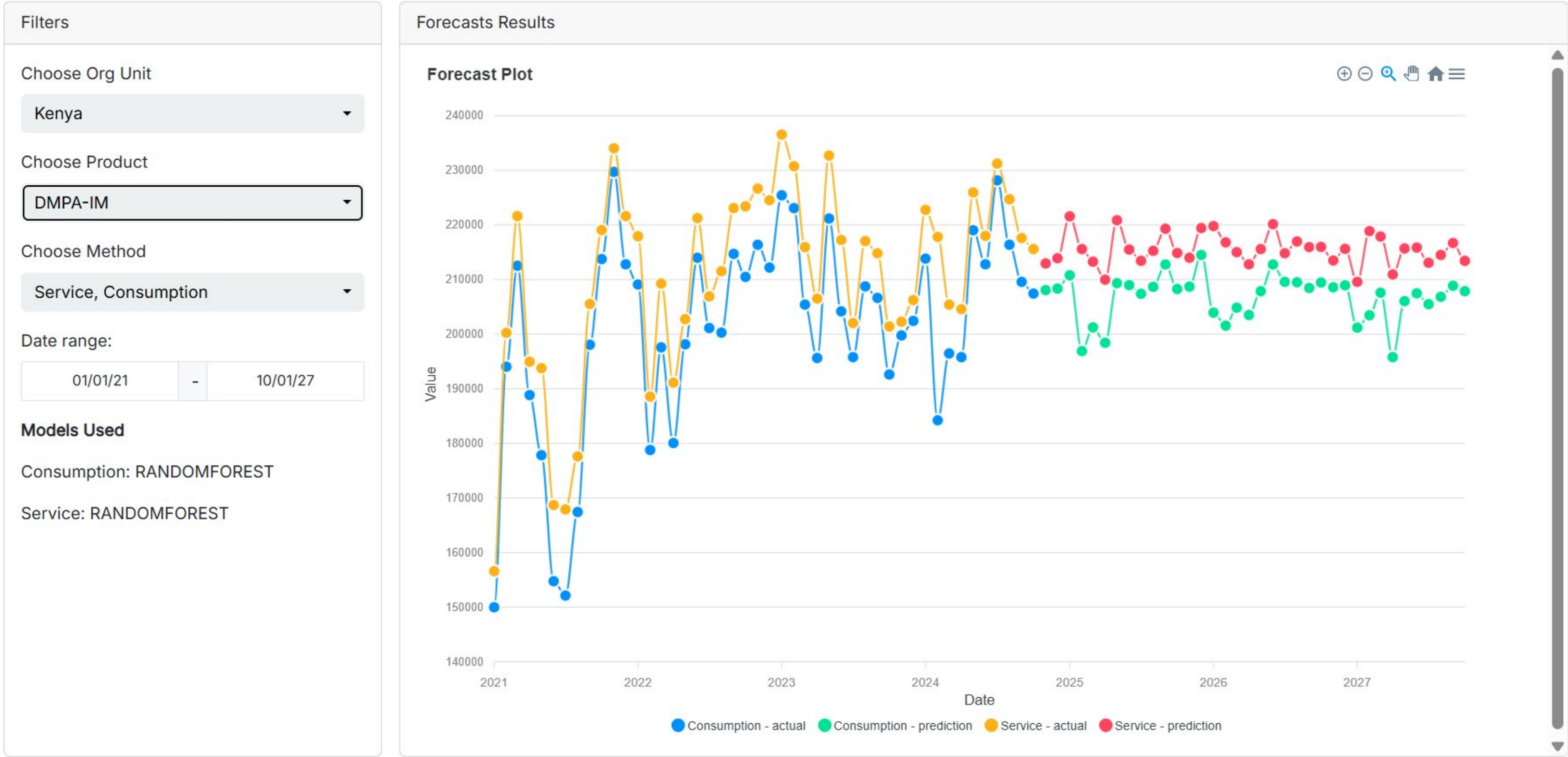
Manual data cleaning posed a barrier to use of time series data. Due to time constraints, teams would only review 12 months of aggregated data per county (47 counties) and visually inspect for outliers (non reporting was not accounted for) before calculating the average monthly consumption (AMC) which was used for estimating requirements

Now the **FP tools** use **60 months (5 years)** of historical data from **10,000+** facilities, and clean data by facility by month as follows:

1. Standardizes the data formatting and/or transforms data into the desired format
2. Identifies and eliminates duplicate records
3. Detects outliers and transforms data
4. Fills in missing values for completeness
5. Adjusts for non-reporting using a predefined calculation method as agreed by stakeholders

Ensuring stakeholder participation and ownership during the process
All tools visualize data pre and post cleaning so that stakeholders can see the changes and approve the use of cleaned data moving forward. This also enables stakeholders to identify and account for context specific factors such as health worker strikes for the different geographies that would be lost when data is used while aggregated.

Machine Learning-Powered Forecasting: At its core, this tool uses powerful machine learning to forecast demand for every family planning commodity. It breaks down predictions by **method – both consumption and services** – and provides this data for both **national and county levels**. Essentially, it makes a really complicated forecasting job much, much simpler.



Live Model Feature: This tool offers a "live model" capability, letting users generate **real-time forecasts on demand**. They can use the data already loaded in the tool, or even pull fresh data straight from KHIS for the most up-to-date projections.

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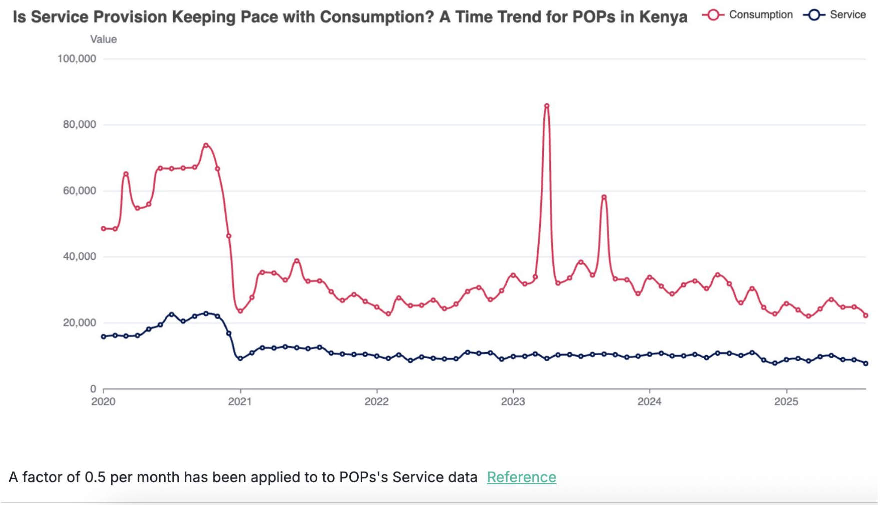
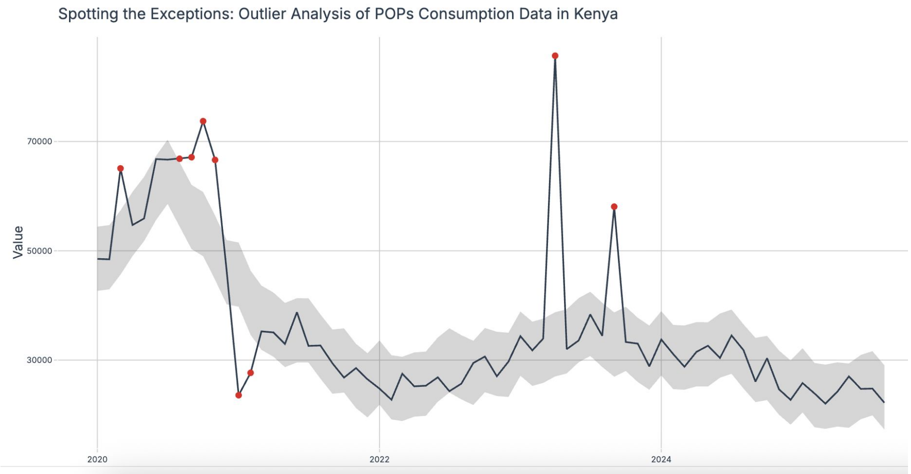
Trend Analysis and Anomaly detection





We've made it easy for users to visualize the historical trends of FP commodities data. This gives users a rapid understanding of past performance and how things have evolved.

The tool also includes a smart feature (**time series decomposition**) for spotting anomalies – or unusual data points. This helps users quickly identify anything that looks out of the ordinary and might need a closer look.

AI Ensures Reliable FP Data for Smarter Forecasting

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Up to 26% anomalies corrected

before forecasting

Product	Method	Data Points	anomalies	Anomaly Rate
Cycle Beads	Consumption	68	18	26.50%
Hormonal IUCD	Consumption	53	12	22.60%
DMPA-IM	Consumption	68	13	19.10%
COCs	Service	68	11	16.20%
Male Condoms	Consumption	68	11	16.20%
COCs	Consumption	68	10	14.70%
Female Condoms	Service	68	10	14.70%

Kenya national FP dataset, 2020 - 2025

- **AI-powered anomaly detection** revealed and corrected up to **27%** of consumption data issues across FP commodities — ensuring budget decisions are based on real demand, not reporting errors.
- The system automatically analyzes **1,699+ data points** across **13 commodities** each month, reducing days of manual review to an instant, repeatable process enabled by a dashboard.
- Data is decomposed into **seasonality, trends, and noise**, allowing the algorithm to identify sudden spikes or drops commonly caused by reporting gaps or stockouts.
- Clean, trustworthy data boosts confidence in forecasting, enabling more accurate procurement and improved product availability for women and families.

AI vs. Manual: The Evidence of Accuracy

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Comparing Mean Absolute Percentage Error (MAPE) for key FP commodities demonstrates AI's superior reliability and efficiency.

METRIC / COMMODITY	AI-GENERATED FORECAST	MANUAL FORECAST	IMPACT / ERROR RATE
Data Processing Time	<10 Minutes	2-3 Days	95%+ Time Saved
DMPA-IM (Consumption)	6.5% MAPE	N/A	High Accuracy
DMPA-SC (Manual)	N/A	26.2% MAPE	~4X Higher Error
LNG Implants, 5-Year	8.6% MAPE	N/A	High Accuracy
LNG Implants, 3-Year (Manual)	N/A	16.6% MAPE	Double the Error
Emergency Pills (ECP)	N/A	103.7% MAPE	Unusable Error Rate

For key products, AI models delivered **significantly higher accuracy** and efficiency, allowing MOH to base procurement decisions on **reliable, evidence-driven predictions.**

Forecast Accuracy Analysis for FP Products Forecasted in 2024

Product	Forecast Methodology	Forecast Error (%)	MAPE (%)	RMSE	Accuracy
DMPA IM	Consumption – AI	-4.96	5.9	14,077	✅ High
DMPA SC	Demographic	29.74	22.9	17,370	❌ Poor
POPs	Consumption – AI	18.11	15.3	6,033	⚠️ Moderate
COCs	Demographic	16.92	13.7	23,226	⚠️ Moderate
ECP	Consumption – AI	-51.79	107.4	3,643	❌ Poor
LNG Implants – 2 Rod (5 yrs)	Consumption – AI	-3.25	9.1	3,932	✅ High
ENG Implants – 1 Rod	Service – AI	11.79	11.5	4,801	⚠️ Moderate
LNG Implants – 2 Rod (3 yrs)	Consumption – AI	21.92	18.7	2,612	⚠️ Moderate
Copper IUCD	Consumption – Excel	-5.41	9.6	708	✅ High
Hormonal IUCD (LNG-IUS)	Service – AI	3.56	23.8	262	❌ Poor
Male Condoms	Demographic	34.91	27.0	977,725	❌ Poor
Female Condoms	Consumption – AI	-19.64	32.1	9,981	❌ Poor
Cycle Beads	Demographic	837.83	89.3	856	❌ Poor

AI is a powerful calculator, not a magician. It exposes, but doesn't fix, the foundational issues of stockouts and data quality.

Findings	What They Mean
Almost half (6 of 13) FP products had poor forecast accuracy; only 3 were highly accurate	Forecast accuracy remains a challenge. AI alone doesn’t solve foundational data and supply chain issues
AI-supported forecasts were not universally more accurate than traditional methods	AI improves efficiency and scale, but strong inputs + expert validation remain essential
Highly accurate forecasts shared 3 traits: • Consumption-based • Reliable historical data • Stable supply/no prolonged stockouts	Data quality + consistent product availability = highest accuracy. AI amplifies good systems
Moderate accuracy often linked to products with stockouts	Stockouts suppress true demand. Supply reliability is critical for accurate forecasting
Low-accuracy forecasts mostly tied to volatile demand or poor/short data history	AI cannot fully overcome unpredictable demand shifts or weak historical data

“The turnaround time improved for data analysis generated from Kenya Health information system (KHIS) to understand consumption trends. It was easy and quick to identify patterns and relationships within historical data to make forecasts for future consumption. Previously it would take at least a day for teams to calculate manually in Excel to generate forecasts. The AI also provided an opportunity to easily simulate and reflect on scenarios such as a seasonality which was difficult and time consuming using Excel sheets. The AI also provided an opportunity to discuss data in detail because less time was used for analysis.” **Daniel Mumbia, M&E officer, DRMH (National FP Quantification team member) Kenya**

From Pilot to Policy: Institutionalizing AI Forecasting (2023–2025)

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2023

Phase 1: Introducing Automation

Time Savings: Reduced manual data processing from days to **<10 minutes**. **Accuracy Gain:** Initial successful pilot, leading to MOH forecasting **7/13 FP products** with AI.

2024

Phase 2 – Scaling and User Confidence

Trust Building: Tool used for official outlier detection and analysis during the National Forecasting Workshop. **Adoption:** MOH officially increased adoption to **8 products**, transitioning the tool into a **trusted decision-support system**.

2025

Phase 3: Full Adoption and Transformation

Institutionalization: Full transition to AI Tool use; for the first time, **national teams did not extract or clean data manually**. **Impact:** AI moved from a project to **institutionalized practice**, ensuring faster, more consistent, and evidence-driven planning.

Key Lessons for Replication: Building Resilient AI Systems

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Blend AI with Human Insight: AI improves accuracy, but human expertise is essential to align forecasts with contextual realities and program changes.

Strengthen Foundational Data Systems: Reliable, complete, and standardized reporting is critical. AI only amplifies the quality of its inputs.

Invest in Capacity & Trust: Training, transparency, and continuous stakeholder engagement are non-negotiable for adoption and long-term sustainability.

Co-Creation is Key for Scale: Early and continuous government ownership (MOH buy-in) fosters integration and ensures the solution is fit-for-purpose and sustainable.

Thank you!

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