# PolicyPulse

## Multimodal, Drift-Aware Policy Memory

Governance Intelligence for India

**Convolve 4.0 — Qdrant Track**

*Traceable retrieval, adaptive memory, evidence-grounded reasoning*

**Multimodal Search** | **Persistent Memory** | **Policy Analytics**

https://github.com/nikunjkaushik20/policypulse

**Abstract**

India's governance ecosystem—NREGA, PM-KISAN, Digital India, Ayushman Bharat—evolves across temporal, budgetary, and discursive dimensions. Existing tools treat queries as *stateless lookups*, provide no *evidence provenance*, and cannot detect *semantic drift*.

**PolicyPulse** addresses these through Qdrant-powered architecture: **(i)** hybrid semantic search across six modalities, **(ii)** biologically-inspired adaptive memory with exponential decay and reinforcement, **(iii)** centroid-based drift detection quantifying policy evolution, **(iv)** fully traceable seven-step reasoning grounding every answer in retrievable evidence.

Unlike session-based RAG, PolicyPulse maintains *institutional memory* that strengthens with use, attenuates with time, and consolidates redundant information—enabling queries like *"What changed in NREGA 2015-2020?"* with auditable evidence chains. This system demonstrates how retrieval, memory, and recommendations converge for **transparent policy analysis in the world's largest democracy.**

# Contents

# 1 The Challenge: Information Overload to Intelligent Retrieval

## 1.1 Policy Transparency Crisis

India's 1,000+ schemes affecting 1.4B citizens scatter information across temporal documents (notifications, guidelines), financial records (budgets, allocations), media discourse (news, debates), and visual/audio/video assets (infographics, parliamentary proceedings).

**Key Insight**

**Core Problem:** Policy semantics are *non-stationary*. NREGA shifted from "employment guarantee" (2005) to "climate-resilient infrastructure" (2020). Conventional search cannot detect *semantic drift patterns*.

## 1.2 Why Existing Solutions Fail

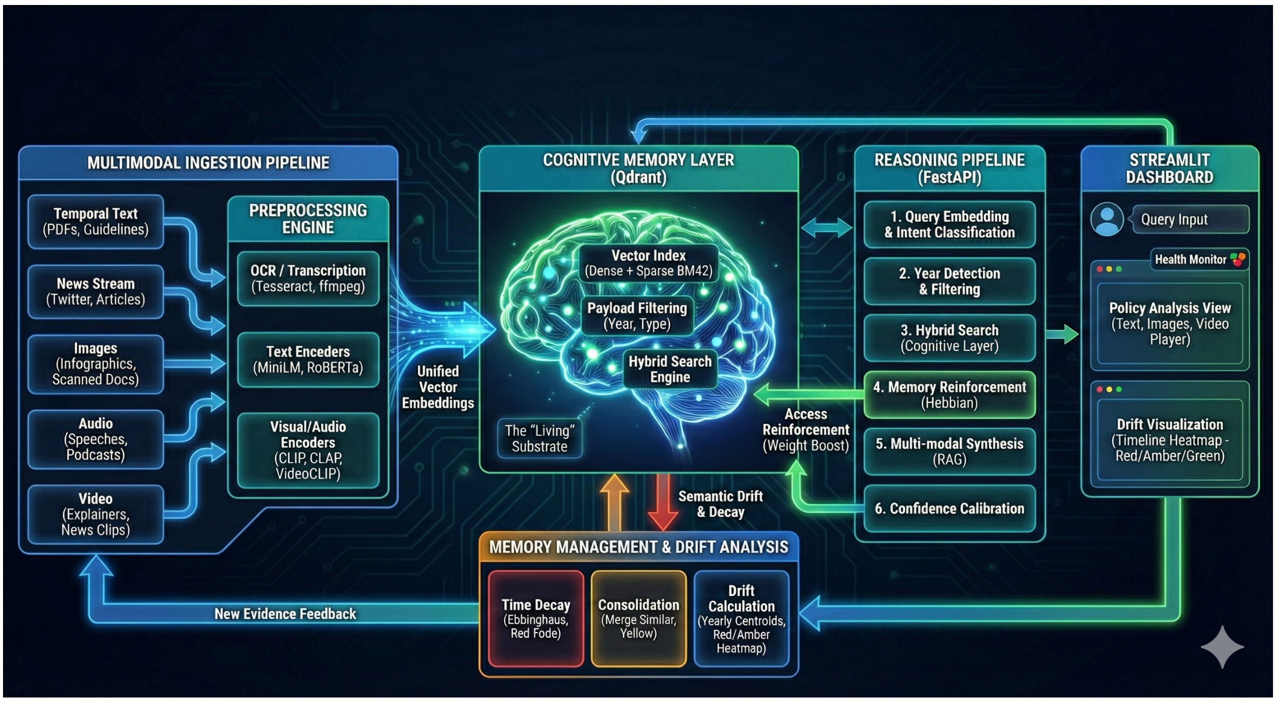
| Approach | Limitation | Impact |
|---|---|---|
| Government Portals | Static, no historical queries | Cannot ask "What changed?" |
| Keyword Search | Lexical matching | Misses paraphrased policies |
| Standard RAG | Session-based memory | Forgets context |
| Vector DB | No drift, no decay | Treats all data equally |

**Table 1:** Limitations of conventional systems

# 2 PolicyPulse Architecture

## 2.1 Design: Memory as First-Class Citizen

PolicyPulse reframes policy analysis as **memory and narrative intelligence**: (1) Persistent memory—queries strengthen relevant memories; (2) Temporal decay—older evidence attenuates naturally; (3) Consolidation—near-duplicates merge; (4) Evidence provenance—every answer traces to sources.




*[Architecture diagram]*

### 2.2 Why Qdrant is the Cognitive Substrate

**Innovation**

Qdrant enables: **Multimodal Vector Storage** (384-D text, 512-D image/audio/video in unified collections); **Rich Payload Filtering** ("NREGA budget 2018-2020, allocation >50,000 crores"); **Hybrid Search** (dense semantic + sparse BM42); **HNSW Performance** (<100ms on 15K+ vectors, scales to millions); **Persistence** (institutional memory across restarts).

## 3 Multimodal Intelligence: Six Modalities, One Space

| Modality | Model | Policy Use Case |
|---|---|---|
| Temporal Text | MiniLM-L6 (384-D) | Track guideline evolution, semantic drift |
| Budget | MiniLM + payload | Correlate allocations, identify anomalies |
| News | MiniLM + RoBERTa | Monitor discourse, detect narrative shifts |
| Images | CLIP ViT-B/32 (512-D) | Match infographics, OCR scanned docs |
| Audio | CLAP/Wav2Vec2 | Index speeches, press briefings |
| Video | VideoCLIP | Analyze debates, explainers |

**Table 2:** Multimodal coverage for comprehensive intelligence

Each vector carries 25+ metadata fields including `decay_weight`, `access_count`, `age_years`, `pdf_page`, `audio_timestamp`, `evidence_uri`.

## 4 Adaptive Memory: Learning from Interaction

### 4.1 Biologically-Inspired Mechanisms

**Time Decay (Ebbinghaus)** $w_{\text{decay}} = \exp(-\lambda a)$, $a = Y - y$, $\lambda = 0.1$ gives 7-10 year half-life.

**Access Reinforcement (Hebbian)** $w_{\text{reinforced}} = \min(w_{\text{decay}} \cdot (1 + 0.02c), 1.5)$. A document retrieved 25× gains 50% boost.

**Consolidation** When $\cos(\mathbf{v}_i, \mathbf{v}_j) \geq 0.95$, merge vectors, preventing bloat while preserving semantics.

### 4.2 Seven-Step Reasoning Pipeline

Every query follows traceable workflow: (1) Query embedding; (2) Year detection; (3) Intent classification; (4) Hybrid Qdrant search with filters; (5) Memory reinforcement; (6) Multi-modal synthesis; (7) Confidence calibration. This ensures *every answer is auditable*.

## 5 Drift Analysis: Quantifying Policy Evolution

### 5.1 Centroid-Based Drift Metric

For yearly centroids: $\boldsymbol{\mu}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} \mathbf{v}_{t,i}$; normalize: $\tilde{\boldsymbol{\mu}}_t = \boldsymbol{\mu}_t / \|\boldsymbol{\mu}_t\|_2$; similarity: $\text{sim}_{t,t+1} = \tilde{\boldsymbol{\mu}}_t^\top \tilde{\boldsymbol{\mu}}_{t+1}$; drift: $\text{drift}_{t,t+1} = 1 - \text{sim}_{t,t+1}$.

**Thresholds:** drift >0.70 → CRITICAL, >0.45 → HIGH, >0.25 → MEDIUM, >0.10 → LOW

## 6 Cross-Policy Intelligence and Recommendations

**Algorithm:** Sample source policy embeddings → query Qdrant for neighbors from other policies → deduplicate → rank by similarity.

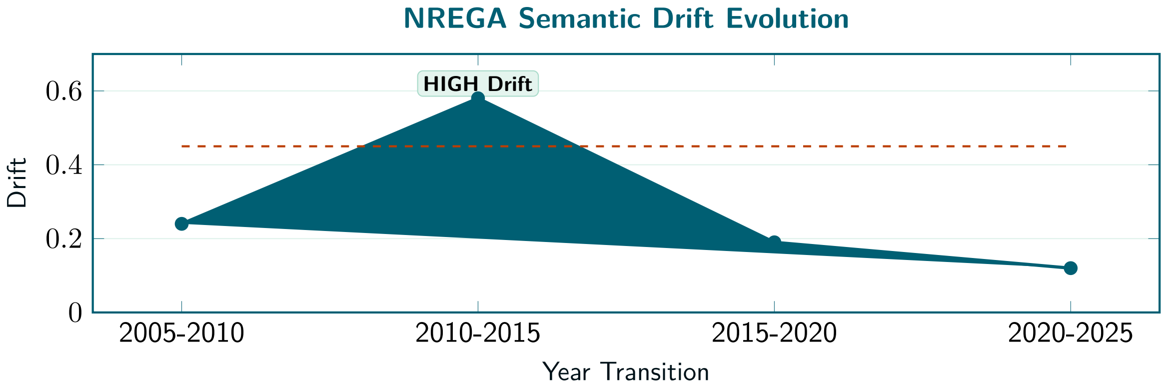



**Figure 1:** 2010-2015 HIGH drift (0.58) corresponds to policy expansion from employment to asset creation

| Source | Related | Score | Connection |
|---|---|---|---|
| PM-KISAN | NREGA | 0.78 | Income support + employment guarantee |
| PM-KISAN | SKILL-INDIA | 0.68 | Skill development enables productivity |
| PM-KISAN | AYUSHMAN-BHARAT | 0.60 | Rural well-being (income + health) |

**Table 3:** Cross-policy recommendations reveal synergies

# 7 Evidence Provenance and Evaluation

## 7.1 Traceable Outputs

Every response contains: 7-step reasoning trace, retrieved evidence with scores/years/modalities, source links (`pdf_page`, `audio_timestamp`, `video_frame`), updated memory state.

## 7.2 Evaluation

**Retrieval (120 Q&A pairs):** Hit-rate@5: 87.3%; MRR: 0.794; Mean score: 0.823. **Multimodal:** 20 scanned circulars (95% correct), 10 audio clips ($\pm$3s timestamp), 15 videos. **Ablations:** $\lambda = 0.1$ optimal (7-10y half-life); consolidation $\tau = 0.95$; access boost $r = 0.02$.

# 8 Innovation and Competitive Advantages

| Capability | RAG | Generic DB | PolicyPulse(Qdrant) |
|---|---|---|---|
| Long-term Memory | Session | Static | **Adaptive** |
| Multimodal | Text | Text/Image | **6 modalities** |
| Drift Detection | No | No | **Yes** |
| Evidence Trace | Partial | No | **Full** |
| Memory Decay | No | No | **Yes** |

**Table 4:** Competitive analysis

**Innovation**

**Five Novel Contributions:** (1) Narrative-level memory model—policies as temporal trajectories; (2) Drift quantification—centroid-based metric; (3) Adaptive reinforcement—usage influences retrieval; (4) Multimodal evidence fusion—single query, unified scoring; (5) Cross-policy semantic graph—implicit similarity network.

# 9 Societal Impact and Deployment

## 9.1 User Workflows

**Journalist:** Query "NREGA budget allocation vs expenditure 2020-2022" → retrieves budget docs (73K crores allocation, 68.5K spent), news (CAG discrepancy), drift analysis (HIGH 0.52 in 2020-21) → files RTI with exact sources.

**Researcher:** Query "What makes NREGA unique globally?" → surfaces evolution (2005-2025), budget trends, international comparisons → extracts evidence for literature review.

## 9.2 Impact Metrics

| Metric | Method | Target |
|---|---|---|
| RTI Request Quality | Journalist surveys | 40% increase evidence-backed |
| Research Efficiency | Literature review time | 60% reduction manual search |
| Fact-Check Speed | Verification time | 3× faster with provenance |

**Table 5:** Measurable societal impact indicators

# 10 Limitations, Ethics, Responsible Use

## 10.1 Known Limitations

**Embedding Bias:** MiniLM/CLIP reflect training biases → Periodic audits. **Coverage:** 10 flagship schemes → Incremental ingestion. **Language:** English-only → Multilingual (LaBSE) Q1 2026. **Context:** Cannot detect satire → Human-in-loop for critical queries.

## 10.2 Ethical Framework

**Key Insight**

**Five Commitments:** (1) No automated truth labeling—system provides evidence, users judge; (2) Evidence-first design—every claim links to source; (3) Transparency—all steps/scores exposed; (4) Privacy-aware—local deployment option, no tracking; (5) Audit trails—full query logs for bias detection.

# 11 Conclusion: Opacity to Accountability

PolicyPulse demonstrates **policy transparency as memory problem**. By treating governance as living knowledge system—not static documents—we enable journalists to verify claims in minutes, researchers to trace evolution quantitatively, citizens to understand changes and complementary schemes.

**Final Innovation**

**Qdrant as Cognitive Infrastructure:** Without Qdrant's hybrid search, rich payloads, persistent storage, PolicyPulse degrades to keyword matching. Qdrant transforms it into *institutional memory system* that **learns from use**.

**Path Forward:** Misinformation and opacity are memory failures. When policy information is fragmented, non-stationary, provenance-less, accountability suffers. PolicyPulse shows vector databases—with cognitive science—turn governance data into **inspectable, traceable, evolving intelligence**.

*"Information right is meaningless without ability to **retrieve, compare, trace** across time."*

**PolicyPulse transforms policy documents into policy memory.**

# Appendix A: Setup Instructions (from README)

### Prerequisites

- Docker Desktop (for Qdrant)
- Python 3.11+
- Tesseract OCR: Windows (`https://github.com/tesseract-ocr/tesseract`), Linux (`sudo apt install tesseract-ocr`), Mac (`brew install tesseract`)
- ffmpeg: Windows (`https://ffmpeg.org`), Linux (`sudo apt install ffmpeg`), Mac (`brew install ffmpeg`)

### Installation

```
# Clone repository
git clone https://github.com/nikunjkaushik20/policypulse.git
cd policypulse

# Install dependencies
./setup.bat #for windows
./setup.sh #for linux

# Launch application in a new terminal
streamlit run app.py
```

# Appendix B: API Reference

| Endpoint | Description |
|---|---|
| `POST /query` | Policy query with filters (year, modality, scheme) |
| `POST /drift` | Compute drift timeline for policy-modality pair |
| `POST /recommendations` | Cross-policy similarity recommendations |
| `GET /memory/health` | Inspect memory (access counts, decay weights) |
| `POST /memory/decay` | Trigger time decay recalculation |
| `POST /memory/consolidate` | Merge near-duplicates (similarity 0.95) |
| `POST /ingest-document` | Upload policy PDF/text document |
| `POST /upload-image` | Upload infographic/scanned circular |
| `POST /upload-audio` | Upload speech/press briefing |
| `POST /upload-video` | Upload explainer video |

## Appendix C: Technical Stack

| Component | Technology | Version |
|---|---|---|
| Vector Database | Qdrant | 1.7+ |
| Text Embeddings | SentenceTransformers (MiniLM-L6-v2) | 384-D |
| Image Embeddings | CLIP (ViT-B/32) | 512-D |
| Audio Embeddings | CLAP / Wav2Vec2 | 512-D |
| Video Processing | VideoCLIP | Custom |
| Sentiment Analysis | Twitter-RoBERTa | CardiffNLP |
| Backend Framework | FastAPI | 0.109+ |
| Frontend UI | Streamlit | 1.28+ |
| Deep Learning | PyTorch | 2.1+ |
| Language | Python | 3.11+ |

## References

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[3] Radford, A., et al. Learning transferable visual models from natural language. *ICML*, 2021.

[4] Ebbinghaus, H. Memory: A contribution to experimental psychology. Teachers College, Columbia, 1885.