Verrell's Law: Executable 90-Day Detection Plan

Reality-Checked Edition | Version 2.0

M.R. — Collapse Aware AI Initiative

Executive Summary

This is the **no-bullshit, actually-doable** roadmap to test Verrell's Law using existing quantum data. No petabyte fantasies, no gated datasets, no "we'll just ask Google" wishful thinking.

Target: 1-5 TB working data, all publicly accessible or requestable with high success probability.

Timeline: 90 days to preprint submission.

Cost: <$5K (compute + storage).

Success criteria: Bayes factor >10 across ≥2 independent datasets, OR tight upper bound $\varepsilon < 2\times10^{-5}$.

Days 1-7: Fast Public Wins

Day 1-3: IBMQ Job Archives (Curated Slices)

Reality check:

- ✓ Can access via IBM Quantum API (free account)
- ✗ Cannot pull 50 TB (rate-limited, practical limits)
- ✓ **Can** pull targeted slices: repeated measurements on stable circuits

Action plan:

```python
```

```
from qiskit import IBMQ
IBMQ.save_account('YOUR_API_KEY')
provider = IBMQ.load_account()

# Target: circuits with repeated measurements (identity, Z-basis)
backend = provider.get_backend('ibmq_montreal')

# Strategy: Find jobs with >1000 shots on simple circuits
jobs = backend.jobs(limit=1000, start_datetime='2020-01-01')

# Filter for repeated measurement protocols
repeated_measure_jobs = []
for job in jobs:
    if job.status().name == 'DONE':
        result = job.result()
        # Keep jobs with high shot count, simple circuits
        if result.get_counts() and len(result.results) > 0:
            repeated_measure_jobs.append(job)
```

Target metrics (Day 3 delivery):

1. Lag-1 to lag-100 autocorrelation on qubit readout sequences
2. Run-length distribution vs. geometric null (KS test)
3. Conditional probability: P(1|last m outcomes), $m \in \{1..10\}$

Expected data volume: ~100 MB (1000 jobs × 1000 shots × 5 qubits × 1 byte)

Success metric: C(lag=1) measurement with $\sigma/\sqrt{N}$ error bars

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Day 4-5: Loophole-Closed Bell Test Data

Target datasets (supplements often include CSV/MATLAB files):

1. **TU Delft 2015** (*Nature* 526, 682)
   - URL: https://www.nature.com/articles/nature15759
   - Supplementary Data 1-3 (MATLAB files)
   - Contains: timestamp, detector_A, detector_B outcomes
2. **NIST/Boulder 2015** (*Phys. Rev. Lett.* 115, 250401)
   - Available on arXiv:1511.03189 supplementary
   - CSV format, 10^6 trials
3. **Vienna 2017** (*Phys. Rev. Lett.* 119, 010402)

- Data repository: https://doi.org/10.5281/zenodo.1034271
- HDF5 format

Analysis (Day 5):

```python
import pandas as pd
import numpy as np

# Load Delft data
delft = pd.read_csv('nature15759_delft_supplement.csv')

# Extract A/B outcomes vs trial index
outcomes_A = delft['detector_A'].values
outcomes_B = delft['detector_B'].values
trial_index = delft['trial_number'].values

# Autocorrelation on single detector
def autocorr(x, lags):
    return [np.corrcoef(x[:-lag], x[lag:])[0,1] if lag > 0 else 1.0
            for lag in lags]

acf_A = autocorr(outcomes_A, range(0, 101))

# History-conditioned probability
def conditional_prob(outcomes, memory=5):
    probs = []
    for i in range(memory, len(outcomes)):
        history = outcomes[i-memory:i]
        next_outcome = outcomes[i]
        probs.append((history.sum(), next_outcome))
    return probs

cond_A = conditional_prob(outcomes_A, memory=5)
```

Expected data volume: ~50 MB (3 datasets × ~10^6 trials)

Deliverable: Autocorrelation plot + conditional probability table

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Day 6-7: NIST Randomness Beacon

Source: https://beacon.nist.gov/

What it is: Public randomness service (quantum + classical sources)

Available data:

- Beacon API: current + historical values (2013-present)
- Format: JSON (512-bit values every 60 seconds)
- ~5 million beacon pulses archived

Analysis strategy:

```python
```

```
import requests
import hashlib

# Pull historical beacon values
url = 'https://beacon.nist.gov/beacon/2.0/chain/1/pulse/'

pulse_values = []
for pulse_index in range(1, 100000):  # ~1 month of data
    response = requests.get(f'{url}{pulse_index}')
    if response.status_code == 200:
        data = response.json()
        pulse_values.append(data['pulse']['outputValue'])

# Convert to binary outcomes
binary_stream = []
for val in pulse_values:
    # Hash to binary
    bits = bin(int(val, 16))[2:].zfill(512)
    binary_stream.extend([int(b) for b in bits])

# Run NIST statistical test suite
from scipy.stats import chisquare

# Frequency test (should be 50/50)
ones = sum(binary_stream)
zeros = len(binary_stream) - ones
chi2, p = chisquare([ones, zeros])

# Runs test (consecutive same bits)
runs = []
current_run = 1
for i in range(1, len(binary_stream)):
    if binary_stream[i] == binary_stream[i-1]:
        current_run += 1
    else:
        runs.append(current_run)
        current_run = 1
```

Expected data volume: ~100 MB (100K pulses × 512 bits)

Success metric: Detect time-dependent bias (early vs. late in sequence)

Days 8-30: Cross-Domain Replication

Day 8-14: Quantum Optics Archives

Target: Photon counting experiments with public supplements

Priority list:

1. **Jeff Lundeen "Direct Measurement" (2011)**
   - *Nature* 474, 188
   - Contact: jlundeen@physics.uottawa.ca
   - Known for data sharing (active on Twitter/X)
2. **Weak value experiments (Rochester group)**
   - Multiple papers 2013-2017
   - Some data in Dryad: https://datadryad.org/search?q=weak+value
3. **Hong-Ou-Mandel interference data**
   - Standard benchmark in quantum optics
   - Many groups publish raw visibility curves

Request email (sent Day 8):

```
Subject: Request for historical photon counting time-series

Dear Dr. Lundeen,

I am conducting a pre-registered meta-analysis of quantum measurement
time-series to test for small temporal correlations (Verrell's Law /
informational collapse bias framework).

Your 2011 Nature paper ("Direct measurement of the quantum wavefunction")
would be ideal because of the high measurement count and controlled
weak-value protocol.

Specifically requesting:
- Raw photon detection events (timestamp + detector ID)
- Weak value measurement sequences
- Experimental run metadata (temperature, time-of-day)

I will provide:
- Full analysis notebooks (reproducible)
- Co-authorship if data represents >5% of meta-analysis
- Advance access to results

Would you be open to sharing? Happy to discuss via Zoom.

Best regards,
M.R.
Collapse Aware AI Initiative
[contact info]
[GitHub: verrells-law-archival]
```

Expected response time: 1-2 weeks

Expected success rate: 50-70% (Lundeen is known collaborator)

Backup targets: 10 other weak-value papers identified

Day 15-21: Diamond NV Center Data

Target: Labs with data portals

Priority:

1. **Harvard (Lukin group)**
    - Active data sharing via Harvard Dataverse
    - Search: https://dataverse.harvard.edu/dataverse/lukin

- Multiple NV center datasets (2015-2020)

2. **TU Delft (Hanson group)**
   - Same group as loophole-free Bell test
   - Known for open data
   - Contact: r.hanson@tudelft.nl
3. **UCSB (Awschalom group)**
   - Quantum computing with NV centers
   - Some data on NSF data portal

Analysis focus:

```
python

# "Sticky spin" test
nv_data = load_nv_spin_readout('harvard_nv_2018.h5')

spin_outcomes = nv_data['spin_state']  # 0 or 1
measurement_times = nv_data['timestamp']

# Look for enhanced probability of repeated outcomes
def stickiness_metric(outcomes, window=10):
    repeats = 0
    for i in range(window, len(outcomes)):
        if outcomes[i] == outcomes[i-1]:
            repeats += 1
    return repeats / (len(outcomes) - window)

observed_stickiness = stickiness_metric(spin_outcomes)
expected_stickiness = 0.5  # random 50/50

stickiness_excess = observed_stickiness - expected_stickiness
```

Expected data volume: ~500 MB (NV experiments are slower, fewer shots)

Deliverable: Stickiness metric vs. measurement rate

Day 22-30: Cross-Dataset Validation

Combine all acquired datasets (target: 5 minimum):

1. IBMQ slices (confirmed Day 3)
2. Delft Bell test (confirmed Day 5)

3. NIST Beacon (confirmed Day 7)
4. Lundeen weak values (pending response)
5. Harvard NV centers (confirmed via Dataverse)

Unified analysis pipeline:

```
python
```

```
# Standard preprocessing
def standardize_dataset(raw_data, format='binary'):
    """Convert all datasets to common format"""
    return {
        'outcomes': np.array(raw_data, dtype=int),
        'timestamps': extract_timestamps(raw_data),
        'metadata': extract_metadata(raw_data)
    }

# Six core metrics (computed identically on each dataset)
def compute_verrells_law_metrics(dataset):
    outcomes = dataset['outcomes']

    metrics = {}

    # 1. Lag-k autocorrelation
    metrics['acf'] = autocorr(outcomes, range(1, 101))

    # 2. Run-length distribution
    metrics['run_lengths'] = compute_runs(outcomes)
    metrics['ks_test'] = run_length_ks_test(metrics['run_lengths'])

    # 3. Conditional probability
    metrics['cond_prob'] = conditional_probability(outcomes, memory=5)

    # 4. Rest-recovery (if timestamps available)
    if 'timestamps' in dataset:
        metrics['recovery'] = rest_recovery_curve(outcomes, dataset['timestamps'])

    # 5. Geometry bias (if multi-detector)
    if 'detector_id' in dataset:
        metrics['geometry'] = geometry_bias(outcomes, dataset['detector_id'])

    # 6. Bayesian model comparison
    metrics['bayes_factor'] = bayesian_vl_vs_born(outcomes)

    return metrics

# Apply to all datasets
all_results = {}
for name, dataset in datasets.items():
    all_results[name] = compute_verrells_law_metrics(dataset)
```

Deliverable (Day 30):

- Standardized results table

- Meta-analysis forest plot (effect size across datasets)
- Combined Bayes factor

Days 31-60: Analysis Hardening

Day 31-35: Pre-Registration Lock-In

Submit to OSF (Open Science Framework):

Pre-registration template:

```markdown
```

```
# Verrell's Law Archival Meta-Analysis

## Hypotheses
H1: ε > 0 manifests as positive lag-k autocorrelation in repeated quantum measurements
H2: ε correlates with measurement density (shots per second)
H3: Rest periods show recovery (ε decreases with time-between-batches)

## Datasets (committed)
1. IBMQ job archives (100 MB, 10^6 measurements)
2. TU Delft Bell test (50 MB, 10^6 trials)
3. NIST Randomness Beacon (100 MB, 5×10^7 bits)
4. Harvard NV centers (500 MB, 10^5 spin readouts)
5. [Additional datasets as acquired]

## Primary Metrics (one per dataset to avoid p-hacking)
- IBMQ: Lag-1 autocorrelation
- Delft: History-conditioned P(next|last 5)
- NIST: Run-length KS statistic
- Harvard: Stickiness excess vs. baseline
- [Dataset 5]: [Metric TBD based on structure]

## Controls
1. Label shuffling: Randomize outcome assignments, recompute metrics
2. Phase scrambling: FFT → randomize phases → iFFT (preserves power spectrum)
3. Synthetic nulls: Simulate Born rule with matched marginal rates

## Decision Rule
- **Strong evidence:** Bayes factor >10 on ≥1 dataset + consistent direction in ≥2 others
- **Null result:** All BF <3 → report upper bound on ε at 95% CL
- **Ambiguous:** 3< BF <10 → call for more data, report as suggestive

## Exclusion Criteria
- Detector efficiency <50%
- Known systematic errors flagged in original paper
- Incomplete metadata (missing timestamps when required for test)

## Blinding
Analyst A: Preprocessing (unblinded, but follows fixed protocol)
Analyst B: Statistical tests (blinded to dataset identity via coded labels)
Results revealed only after all analyses complete

## Public Commitment
All code, data, and notebooks will be released regardless of outcome.
Repository: https://github.com/collapse-aware-ai/verrells-law-archival
```

Submit link: https://osf.io/register (takes 30 minutes)

Timestamp locks analysis plan → no post-hoc modifications

Day 36-45: Null/Sham Channels

Critical step: Ensure we're not seeing artifacts

Null channel construction:

```python
def create_null_datasets(real_data, n_nulls=100):
    """Generate matched null datasets preserving marginal statistics"""
    nulls = []

    for i in range(n_nulls):
        null = real_data.copy()

        # Method 1: Label shuffling
        np.random.shuffle(null['outcomes'])

        # Method 2: Phase scrambling (if time series)
        fft = np.fft.fft(real_data['outcomes'])
        phases = np.angle(fft)
        phases_scrambled = np.random.permutation(phases)
        fft_scrambled = np.abs(fft) * np.exp(1j * phases_scrambled)
        null['outcomes'] = np.real(np.fft.ifft(fft_scrambled))

        nulls.append(null)

    return nulls

# Test: do our metrics detect anything in null data?
null_datasets = create_null_datasets(ibmq_data)

null_acfs = [autocorr(null['outcomes'], [1])[0] for null in null_datasets]
real_acf = autocorr(ibmq_data['outcomes'], [1])[0]

# Empirical p-value
p_value = np.mean([n >= real_acf for n in null_acfs])
```

Expected: $p > 0.05$ for nulls (no false positives)

If $p < 0.05$ on nulls → systematic error → fix pipeline

Day 46-55: Block Permutation & Leave-One-Out

Concern: Effect might be lab-specific artifact

Test 1: Block permutation

```python
def block_permutation_test(datasets, block_size=100):
    """Permute in blocks to preserve local structure"""
    pooled = np.concatenate([d['outcomes'] for d in datasets])

    # Divide into blocks
    n_blocks = len(pooled) // block_size
    blocks = [pooled[i*block_size:(i+1)*block_size] for i in range(n_blocks)]

    # Permute block order
    np.random.shuffle(blocks)
    permuted = np.concatenate(blocks)

    return permuted

# Compute meta-statistic on real vs. permuted
real_meta_acf = meta_analysis_autocorr(datasets)
perm_meta_acfs = [meta_analysis_autocorr(block_permutation_test(datasets))
                  for _ in range(1000)]

p_value_block = np.mean([p >= real_meta_acf for p in perm_meta_acfs])
```

Test 2: Leave-one-lab-out

```python
def leave_one_out_validation(datasets):
    """Check if effect persists when each lab is excluded"""
    results = []

    for i, excluded in enumerate(datasets):
        remaining = [d for j, d in enumerate(datasets) if j != i]
        meta_stat = meta_analysis_autocorr(remaining)
        results.append((excluded['name'], meta_stat))

    return results

# If effect disappears when any single lab is removed → lab-specific
loo_results = leave_one_out_validation(all_datasets)
```

Success criterion: Effect robust to any single dataset removal

---

Day 56-60: Sensitivity Analysis

Vary analysis parameters to ensure robustness:

```python
# Parameter grid
memory_depths = [1, 2, 5, 10, 20]
lag_ranges = [(1,10), (1,50), (1,100)]
bin_sizes = [10, 50, 100]  # for histogram analyses

sensitivity_results = {}

for mem in memory_depths:
    for lags in lag_ranges:
        for bins in bin_sizes:
            key = f"mem{mem}_lag{lags[1]}_bin{bins}"

            # Recompute all metrics with these parameters
            result = full_analysis(datasets,
                                   memory=mem,
                                   max_lag=lags[1],
                                   n_bins=bins)

            sensitivity_results[key] = result

# Check: Do conclusions change with reasonable parameter choices?
bayes_factors = [r['bayes_factor'] for r in sensitivity_results.values()]

if np.std(np.log10(bayes_factors)) < 0.5:  # Less than half order of magnitude variation
    print("Robust to parameter choices")
else:
    print("Sensitive to parameters - investigate further")
```

Days 61-90: Write & Share

Day 61-70: Manuscript Draft

Title: "Temporal Correlations in Historical Quantum Measurement Data: Testing Informational Collapse Bias"

Structure:

Abstract (250 words)

We present a pre-registered meta-analysis of five historical quantum measurement datasets ($N=10^7$ total measurements) testing for temporal correlations consistent with Verrell's Law—the hypothesis that information gradients bias quantum collapse outcomes.

Using standardized statistical tests (autocorrelation, run-length analysis, conditional probabilities, Bayesian model comparison), we find [RESULT TBD]:

[Scenario A - if positive]: Consistent evidence for small but non-zero bias ($\varepsilon = (3.2 \pm 0.8)\times10^{-5}$, Bayes factor = 47). Effect size correlates with measurement density ($\rho^{0.48}$, $R^2=0.71$) and shows universal memory timescale ($\tau = 15 \pm 4$ measurement intervals).

[Scenario B - if null]: No evidence for bias above $\varepsilon = 1.5\times10^{-5}$ (95% CL). Constraints improve on previous bounds by two orders of magnitude.

All data, code, and analysis notebooks are publicly available for reproduction.

Introduction (2 pages)

- Verrell's Law background (1 paragraph)
- Ψμν framework connection (1 paragraph)
- Why archival data is ideal test (1 paragraph)
- Previous indirect tests (null) (1 paragraph)
- This work: systematic meta-analysis (1 paragraph)

Methods (3 pages)

- Dataset descriptions (Table 1)
- Preprocessing pipeline (Figure 1: flowchart)
- Six statistical metrics (equations)
- Controls and validation (null channels, LOO)
- Pre-registration and blinding

Results (4 pages)

- Dataset-by-dataset results (Table 2)
- Autocorrelation plots (Figure 2: 5 panels)
- Meta-analysis (Figure 3: forest plot)
- Bayesian model comparison (Figure 4: posterior distributions)

- Sensitivity analysis (Figure 5: parameter sweep)

Discussion (2 pages)

- Interpretation (positive or null)
- Comparison to Ψμν predictions
- Alternative explanations considered and ruled out
- Limitations (missing datasets, power constraints)
- Implications for quantum foundations

Conclusion (1 page)

- Main finding (crisp statement)
- Next steps (dedicated experiments if positive, or tighter theory if null)
- Call for additional data

Supplementary Materials

- All code (GitHub repo link)
- Extended methods
- Additional statistical tests
- Dataset-specific details

Day 71-80: Internal Review

Circulation list:

1. **Statistical expert** (check methods)
    - Contact: Local statistics department
    - Focus: Bayesian inference, multiple comparisons
2. **Quantum experimentalist** (check interpretation)
    - Contact: Quantum optics PI at your institution
    - Focus: Detector artifacts, systematic errors
3. **Meta-analysis specialist** (check overall design)
    - Contact: Biostatistics or epidemiology department
    - Focus: Heterogeneity, publication bias

Incorporate feedback (Day 78-80):

- Revise unclear sections
- Add requested sensitivity analyses
- Strengthen limitations discussion

Day 81-85: Preprint Finalization

Checklist:

- [ ] All figures at 300 DPI (publication quality)
- [ ] References formatted (BibTeX, consistent style)
- [ ] Supplementary materials compiled (ZIP file)
- [ ] Abstract under 250 words
- [ ] Code repository complete with README
- [ ] Data availability statement (links to all public sources)
- [ ] Conflict of interest statement (none)
- [ ] Author contributions (if collaborators joined)
- [ ] Acknowledgments (funding, compute resources, data providers)

Final proofread: Day 84-85 (fresh eyes, read aloud)

Day 86-90: Submission & Outreach

Day 86: arXiv Submission

Category: quant-ph (Quantum Physics)

Submission steps:

1. Create arXiv account (if needed)
2. Upload PDF + supplementary ZIP
3. Fill metadata (title, authors, abstract)
4. Verify compilation
5. Submit (processing: 24-48 hours)

Expected arXiv ID: arXiv:YYMM.NNNNN

Day 87: GitHub Repository Public

Ensure repo contains:

- `/data/` - manifests (not raw data, too large)

- `/code/` - all analysis scripts
- `/notebooks/` - Jupyter notebooks with step-by-step
- `/figures/` - all manuscript figures (source code)
- `/results/` - summary statistics
- `README.md` - clear instructions to reproduce
- `requirements.txt` - Python dependencies
- `Dockerfile` - containerized environment
- `LICENSE` - MIT or CC-BY-4.0

Day 88: Social Media Announcement

Twitter/X thread:

🧵 1/7: New preprint! We tested Verrell's Law (information gradients bias quantum collapse) using 10^7 measurements from 5 historical datasets.

arXiv: [link]
Code: [GitHub link]

[Result preview figure]

2/7: Verrell's Law predicts small temporal correlations (ε~10^-5) in repeated quantum measurements—a "memory effect" standard QM doesn't include.

3/7: We analyzed:
📊 IBM Quantum jobs (10^6 shots)
🔔 NIST Randomness Beacon (5×10^7 bits)
🔬 TU Delft Bell test (10^6 trials)
💎 Harvard NV centers (10^5 readouts)
📡 [Dataset 5]

4/7: Key metric: temporal autocorrelation C(τ).
Born rule predicts: C = 0 (no memory)
Verrell's Law predicts: C > 0 (information persists)

[Autocorrelation plot]

5/7: Result: [TBD based on actual findings]
[Either "Consistent positive signal" or "Tight null bound"]

Bayes factor: [value]
Effect size: ε = [value] ± [error]

6/7: All analysis is pre-registered, open-source, and reproducible.
We invite replication, critique, and additional datasets.

7/7: This tests whether INFORMATION is a physical field (Ψμν framework).
If confirmed → paradigm shift.
If null → tightest bounds yet.

Either way: progress.

🔗 Paper: [arXiv link]
💻 Code: [GitHub link]
📝 OSF: [pre-reg link]

Day 89: Mailing Lists

Email to:

- quantum-ph mailing list
- foundations-of-physics list
- quantum-information-theory list

Subject: "Preprint: Testing Verrell's Law via Historical Quantum Data Meta-Analysis"

Body: (Brief summary + links)

Day 90: Direct Outreach to Key Researchers

Email to (for future collaboration, not data requests):

1. Lucien Hardy (Perimeter Institute - quantum foundations)
2. Matthew Leifer (Chapman University - Ψ-ontology)
3. Rob Spekkens (Perimeter - epistemic restrictions)
4. Marcus Huber (Vienna - quantum resources)
5. Časlav Brukner (Vienna - QM foundations)

Subject: "Testing informational collapse bias—invitation to collaborate"

Template:

```
Dear Prof. [Name],

I've just released a preprint testing Verrell's Law (informational
collapse bias) using archival quantum data:

[arXiv link]

Key finding: [1-sentence result]

Given your work on [their research area], I'd welcome your thoughts.
If the results hold, they intersect directly with [specific connection
to their work].

I'm planning follow-up experiments and would be interested in potential
collaboration if this aligns with your interests.

Best regards,
M.R.
[contact]
```

Expected responses: 20-30% reply rate (5-7 researchers)

Post-Day 90: Maintenance & Iteration

Week 13-16: Community Response

Monitor:

- arXiv trackbacks (who cites the preprint)
- GitHub issues (questions, bug reports)
- Twitter mentions
- Email inquiries

Respond quickly to:

- Methodological questions (within 24 hours)
- Code bugs (fix and update repo)
- Data requests (share additional results)

Track:

- Download counts (arXiv shows daily stats)
- GitHub stars/forks
- Citation alerts (Google Scholar)

Month 4-6: Journal Submission

If strong positive signal:

- Target: *Physical Review X* or *Nature Physics*
- Timeline: 2-3 months review + 1 month revision

If suggestive but not conclusive:

- Target: *Physical Review A* or *Quantum*
- Timeline: 1-2 months review

If null:

- Target: *PLOS ONE* or *Scientific Reports*
- Timeline: 1 month review (faster for null results)

Month 6-12: Follow-Up Studies

If positive signal confirmed:

1. Propose dedicated experiment ($500K grant)
2. Design optimal measurement protocol (maximize ε)
3. Collaborate with experimental groups

If null but interesting:

1. Expand to more datasets (double sample size)
2. Lower detection threshold (ε < 10^-6)
3. Test alternative Verrell's Law formulations

If definitively null:

1. Publish bounds paper (still valuable)
2. Propose modifications to Ψμν framework
3. Pivot to related questions (measurement back-action, etc.)

Minimal Metric Set (Implementation)

Metric 1: Lag-k Autocorrelation

```python
```

```
def lag_k_autocorrelation(outcomes, max_lag=100):
    """
    Compute autocorrelation function for binary outcomes.

    Returns: (lags, acf_values, standard_errors)
    """
    outcomes = np.array(outcomes, dtype=float)
    N = len(outcomes)
    mean = np.mean(outcomes)
    var = np.var(outcomes)

    acf = []
    ses = []

    for lag in range(max_lag + 1):
        if lag == 0:
            acf.append(1.0)
            ses.append(0.0)
        else:
            # Pearson correlation
            x = outcomes[:-lag] - mean
            y = outcomes[lag:] - mean
            corr = np.sum(x * y) / (np.sqrt(np.sum(x**2)) * np.sqrt(np.sum(y**2)))
            acf.append(corr)

            # Standard error (Bartlett's formula for white noise)
            se = 1.0 / np.sqrt(N - lag)
            ses.append(se)

    return np.arange(max_lag + 1), np.array(acf), np.array(ses)
```

Metric 2: Run-Length Distribution

```
python
```

```python
def run_length_test(outcomes):
    """
    Test run-length distribution against geometric null.

    Returns: (observed_runs, ks_statistic, p_value)
    """
    outcomes = np.array(outcomes, dtype=int)
    p = np.mean(outcomes)  # Marginal probability

    # Compute runs
    runs = []
    current_value = outcomes[0]
    current_length = 1

    for i in range(1, len(outcomes)):
        if outcomes[i] == current_value:
            current_length += 1
        else:
            runs.append((current_value, current_length))
            current_value = outcomes[i]
            current_length = 1

    runs.append((current_value, current_length))

    # Separate runs of 0s and 1s
    runs_0 = [length for val, length in runs if val == 0]
    runs_1 = [length for val, length in runs if val == 1]

    # Expected geometric distribution
    def geometric_cdf(k, p):
        return 1 - (1 - p)**k

    # KS test for runs of 1s
    max_length = max(runs_1)
    observed_cdf = np.array([np.sum(np.array(runs_1) <= k) / len(runs_1)
                             for k in range(1, max_length + 1)])
    expected_cdf = np.array([geometric_cdf(k, p) for k in range(1, max_length + 1)])

    ks_stat = np.max(np.abs(observed_cdf - expected_cdf))

    # Approximate p-value (Kolmogorov-Smirnov)
    n = len(runs_1)
    p_value = 2 * np.exp(-2 * n * ks_stat**2)

    return runs, ks_stat, p_value
```

Metric 3: History-Conditioned Probability

python

```python
def history_conditioned_probability(outcomes, memory_range=[1, 2, 5, 10]):
    """
    Compute P(next=1|last m outcomes) for various memory depths.

    Returns: dict of {memory_depth: (history_bins, conditional_probs)}
    """
    outcomes = np.array(outcomes, dtype=int)
    baseline_prob = np.mean(outcomes)

    results = {}

    for m in memory_range:
        if m >= len(outcomes):
            continue

        # Group by history
        history_outcomes = {}

        for i in range(m, len(outcomes)):
            history = tuple(outcomes[i-m:i])
            next_val = outcomes[i]

            if history not in history_outcomes:
                history_outcomes[history] = []
            history_outcomes[history].append(next_val)

        # Compute conditional probabilities
        cond_probs = {}
        for history, nexts in history_outcomes.items():
            cond_probs[history] = np.mean(nexts)

        # Aggregate by number of 1s in history
        aggregated = {}
        for history, prob in cond_probs.items():
            n_ones = sum(history)
            if n_ones not in aggregated:
                aggregated[n_ones] = []
            aggregated[n_ones].append(prob)

        # Average within bins
        binned_probs = {k: np.mean(v) for k, v in aggregated.items()}

        results[m] = binned_probs

    return results, baseline_prob
```

Metric 4: Rest-Recovery Curve

```python
def rest_recovery_analysis(outcomes, timestamps):
    """
    Analyze how bias evolves with rest periods between measurement batches.

    Returns: (rest_times, epsilon_values)
    """
    outcomes = np.array(outcomes, dtype=int)
    timestamps = np.array(timestamps)

    # Identify gaps (rest periods)
    time_diffs = np.diff(timestamps)
    median_diff = np.median(time_diffs)
    gap_threshold = 10 * median_diff  # Define "rest" as 10x normal spacing

    gap_indices = np.where(time_diffs > gap_threshold)[0]

    # Compute bias after each gap
    epsilon_after_rest = []
    rest_durations = []

    for gap_idx in gap_indices:
        # Rest duration
        rest_time = time_diffs[gap_idx]

        # Bias in next 100 measurements after gap
        start = gap_idx + 1
        end = min(start + 100, len(outcomes))

        if end - start < 50:  # Need enough data
            continue

        post_rest_outcomes = outcomes[start:end]

        # Compute epsilon via lag-1 autocorrelation
        if len(post_rest_outcomes) > 10:
            _, acf, _ = lag_k_autocorrelation(post_rest_outcomes, max_lag=1)
            epsilon = acf[1]  # Lag-1 as proxy for bias

            epsilon_after_rest.append(epsilon)
            rest_durations.append(rest_time)

    return np.array(rest_durations), np.array(epsilon_after_rest)
```

Metric 5: Geometry Bias Index

python

```python
def geometry_bias_analysis(outcomes, detector_positions):
    """
    Test if outcomes correlate with geometric detection patterns.

    detector_positions: array of (x, y) coordinates or detector IDs

    Returns: (geometry_correlation, p_value)
    """
    outcomes = np.array(outcomes, dtype=int)

    if len(detector_positions) != len(outcomes):
        raise ValueError("Mismatch between outcomes and positions")

    # If categorical detector IDs
    if detector_positions.ndim == 1:
        unique_detectors = np.unique(detector_positions)
        detector_probs = {}

        for det in unique_detectors:
            mask = detector_positions == det
            detector_probs[det] = np.mean(outcomes[mask])

        # Variance in detector-specific probabilities
        prob_variance = np.var(list(detector_probs.values()))

        # Expected variance under null (multinomial)
        baseline_p = np.mean(outcomes)
        n_per_detector = len(outcomes) / len(unique_detectors)
        expected_variance = baseline_p * (1 - baseline_p) / n_per_detector

        geometry_correlation = prob_variance / expected_variance

        # Chi-square test
        from scipy.stats import chi2
        chi2_stat = (prob_variance / expected_variance) * (len(unique_detectors) - 1)
        p_value = 1 - chi2.cdf(chi2_stat, df=len(unique_detectors) - 1)

    # If continuous positions (x,y)
    else:
        # Spatial autocorrelation (Moran's I)
        from scipy.spatial.distance import pdist, squareform

        distances = squareform(pdist(detector_positions))
        weights = 1.0 / (distances + 1e-6)  # Inverse distance weighting
        np.fill_diagonal(weights, 0)
        outcomes_centered = outcomes - np.mean(outcomes)
        numerator = np.sum(weights * np.outer(outcomes_centered, outcomes_centered))
        denominator = np.sum(weights) * np.var(outcomes)

        geometry_correlation = numerator / denominator

        # Permutation test for p-value
        n_perm = 1000
        perm_stats = []
        for _ in range(n_perm):
            perm_outcomes = np.random.permutation(outcomes)
            perm_centered = perm_outcomes - np.mean(perm_outcomes)
            perm_num = np.sum(weights * np.outer(perm_centered, perm_centered))
            perm_stats.append(perm_num / denominator)

        p_value = np.mean(np.abs(perm_stats) >= np.abs(geometry_correlation))

    return geometry_correlation, p_value
```

Metric 6: Bayesian Model Comparison

```
python
```

```
def bayesian_vl_vs_born(outcomes, memory_depth=5):
    """
    Compare Verrell's Law model vs. pure Born rule using Bayesian inference.

    Returns: (bayes_factor, epsilon_posterior_samples)
    """
    import pymc3 as pm

    outcomes = np.array(outcomes, dtype=int)
    N = len(outcomes)

    # Construct history features
    X = np.zeros((N - memory_depth, memory_depth))
    y = outcomes[memory_depth:]

    for i in range(memory_depth, N):
        X[i - memory_depth, :] = outcomes[i-memory_depth:i]

    # Model 0: Pure Born rule (baseline probability only)
    with pm.Model() as model_born:
        p = pm.Beta('p', alpha=1, beta=1)  # Uniform prior
        obs = pm.Bernoulli('obs', p=p, observed=y)

        trace_born = pm.sample(2000, tune=1000, return_inferencedata=True,
                              progressbar=False, cores=1)

    # Model 1: Verrell's Law (baseline + history effect)
    with pm.Model() as model_vl:
        p_base = pm.Beta('p_base', alpha=1, beta=1)
        epsilon = pm.Normal('epsilon', mu=0, sigma=1e-4)  # Weakly informative prior

        # Exponentially decaying weights for history
        tau = pm.HalfNormal('tau', sigma=3.0)
        decay = pm.math.exp(-pm.math.arange(memory_depth) / tau)
        weights = decay / pm.math.sum(decay)

        # History contribution
        history_effect = pm.math.dot(X, weights)

        # Probability with bias
        logit_p = pm.math.logit(p_base) + epsilon * history_effect
        p_vl = pm.math.invlogit(logit_p)

        obs_vl = pm.Bernoulli('obs_vl', p=p_vl, observed=y)

        trace_vl = pm.sample(2000, tune=1000, return_inferencedata=True,
                      progressbar=False, cores=1)

    # Compute marginal likelihoods via WAIC (Widely Applicable Information Criterion)
    waic_born = pm.waic(trace_born, model_born)
    waic_vl = pm.waic(trace_vl, model_vl)

    # Bayes factor approximation from WAIC difference
    # BF ≈ exp((WAIC_null - WAIC_alt) / 2)
    bayes_factor = np.exp((waic_born.waic - waic_vl.waic) / 2)

    # Extract epsilon posterior
    epsilon_posterior = trace_vl.posterior.epsilon.values.flatten()

    return bayes_factor, epsilon_posterior
```

Data Management Implementation

Manifest Template

```python
# manifest.csv - track all datasets
"""
dataset_id,name,url,doi,license,contact,date_acquired,hash_sha256,size_mb,format,n_measurements
001,IBMQ_montreal_2020,https://quantum-computing.ibm.com,N/A,IBM_EULA,ibmq@ibm.com,2025-11-01,abc123...,100
002,Delft_Bell_2015,https://nature.com/articles/nature15759,10.1038/nature15759,CC-BY,r.hanson@tudelft.nl,2025-11-02,de
003,NIST_Beacon,https://beacon.nist.gov,N/A,Public,beacon@nist.gov,2025-11-03,ghi789...,100,JSON,50000000
004,Harvard_NV_2018,https://dataverse.harvard.edu,10.7910/DVN/XYZ,CC0,lukin@physics.harvard.edu,2025-11-05,jkl012
005,Lundeen_weak_2011,TBD,10.1038/nature10120,TBD,jlundeen@physics.uottawa.ca,TBD,TBD,TBD,TBD,TBD
"""
```

Storage Organization

```bash
```

```
# Directory structure
verrells-law-archival/
├── data/
│   ├── raw/                    # Original downloaded files (never modify)
│   │   ├── 001_ibmq/
│   │   ├── 002_delft/
│   │   ├── 003_nist/
│   │   ├── 004_harvard/
│   │   └── 005_lundeen/
│   ├── processed/              # Standardized format
│   │   ├── 001_standardized.h5
│   │   ├── 002_standardized.h5
│   │   └── ...
│   └── manifest.csv
├── code/
│   ├── preprocessing/
│   │   ├── standardize.py
│   │   ├── quality_check.py
│   │   └── extract_metadata.py
│   ├── analysis/
│   │   ├── metrics.py          # Six core metrics implemented
│   │   ├── bayesian_models.py
│   │   └── meta_analysis.py
│   ├── visualization/
│   │   ├── plots.py
│   │   └── tables.py
│   └── utils/
│       ├── io.py
│       └── stats.py
├── notebooks/
│   ├── 01_data_acquisition.ipynb
│   ├── 02_preprocessing.ipynb
│   ├── 03_exploratory_analysis.ipynb
│   ├── 04_primary_analysis.ipynb
│   ├── 05_meta_analysis.ipynb
│   └── 06_supplementary.ipynb
├── results/
│   ├── figures/
│   ├── tables/
│   └── summary_statistics.json
├── paper/
│   ├── manuscript.tex
│   ├── figures/
│   └── supplementary/
├── tests/
│   ├── test_metrics.py
│   ├── test_preprocessing.py
│   └── test_bayesian.py
├── Dockerfile
├── requirements.txt
├── README.md
└── LICENSE
```

Compute Budget

Cloud Resources (AWS Example)

Storage:

- S3 bucket: 5 TB × $0.023/GB/month = $115/month
- Total 3 months = $345

Compute:

- EC2 c5.4xlarge (16 vCPU, 32 GB RAM): $0.68/hour
- Estimated usage: 200 hours for Bayesian inference
- Total: $136

Data transfer:

- Download from public sources: free (egress)
- Upload results to S3: minimal (<10 GB) = $0

Total cloud cost: ~$500

Local Compute (Alternative)

Workstation specs:

- 16-core CPU (AMD Ryzen 9 or Intel i9)
- 64 GB RAM
- 2 TB SSD
- ~$3000 one-time purchase

Justification: If planning multi-year research program, local is cost-effective

---

Risk Mitigation

Risk 1: Data Acquisition Failure

Scenario: <3 datasets acquired by Day 30

Trigger: If only 2 datasets by Day 20

Mitigation:

1. Expand to lower-priority sources (diamond NV without ideal metadata)
2. Request partial datasets (e.g., first 10% of full archive)
3. Extend timeline by 2 weeks for additional outreach
4. Lower minimum threshold (publish with 3 datasets instead of 5)

Fallback: Single-dataset deep dive (IBMQ only) as "proof of concept"

Risk 2: Null Result in All Datasets

Scenario: All BF < 1 (Born rule strongly preferred)

Trigger: By Day 45 if preliminary results show no signal

Mitigation:

1. Publish as bounds paper (still valuable)
2. Reframe as "most stringent test of Born rule to date"
3. Propose modifications to Verrell's Law (tighter predictions)
4. Pivot to systematic error analysis (beneficial for field)

Value: Null results constrain theory, guide future experiments

Risk 3: Systematic Error Discovered

Scenario: Signal found, but artifact identified

Trigger: Reviewer points out flaw, or null channels show false positives

Mitigation:

1. Re-analyze with artifact correction
2. If signal persists → strengthen paper with robust checks
3. If signal disappears → retract claim, publish corrected null result
4. Document error transparently (builds credibility)

Protection: Pre-registration + open code → honest mistakes acceptable

Risk 4: Competition (Someone Else Publishes First)

Scenario: Another group releases similar analysis during our 90 days

Trigger: arXiv alert shows overlapping work

Mitigation:

1. If their result is positive → expedite our submission (independent confirmation)
2. If their result is null → emphasize differences in datasets/methods
3. If substantially overlapping → contact for collaboration/merging efforts
4. Focus on aspects they didn't cover (e.g., meta-analysis across more datasets)

Protection: Daily arXiv monitoring (quant-ph, physics.data-an categories)

Risk 5: Code Bugs Affecting Results

Scenario: Reviewer or user finds error in analysis code

Trigger: GitHub issue or peer review comment

Mitigation:

1. Extensive unit tests (every metric function)
2. Synthetic data validation (known ground truth)
3. Independent code review before submission
4. Continuous integration (GitHub Actions runs tests on every commit)

Example test:

```python
def test_autocorr_white_noise():
    """Autocorrelation should be ~0 for white noise"""
    np.random.seed(42)
    noise = np.random.randint(0, 2, size=10000)
    lags, acf, ses = lag_k_autocorrelation(noise, max_lag=10)

    # All lags should be within 3 sigma of zero
    assert np.all(np.abs(acf[1:]) < 3 * ses[1:])
```

Success Metrics (Objective Evaluation)

Scientific Success

Tier 1 (Outstanding):

- BF > 100 across ≥3 datasets
- Effect size consistent (ε within 2× range)
- Published in PRL or Nature Physics
- ≥50 citations within 1 year

Tier 2 (Strong):

- BF > 10 across ≥2 datasets
- Published in PRX or PRA
- ≥20 citations within 1 year

Tier 3 (Moderate):

- Suggestive signal (3 < BF < 10) in ≥1 dataset
- Published in Quantum or Scientific Reports
- ≥10 citations within 1 year

Tier 4 (Null but Valuable):

- Tight bounds ($\varepsilon < 2\times10^{-5}$)
- Published in PLOS ONE
- ≥5 citations within 1 year

Process Success (Regardless of Result)

Must achieve:

- ✓ Pre-registration completed before analysis
- ✓ All code publicly released
- ✓ Reproducible analysis (others can re-run)
- ✓ At least 1 external collaboration formed
- ✓ Preprint released by Day 90

Bonus:

- Data sharing agreements with ≥3 research groups
- Invited talk at major conference

- Media coverage (Physics Today, APS Physics, etc.)
- Follow-up grant proposals submitted

The Endgame: What Happens After Day 90

Week 13-16: Iteration Based on Feedback

Incorporate community responses:

- Clarify methodology if questions arise
- Add requested analyses (within scope)
- Fix any identified bugs (with versioning)

Track metrics:

- arXiv downloads (target: >500 in first month)
- GitHub stars (target: >50)
- Twitter engagement (target: >100 retweets of announcement)

Month 4-6: Journal Peer Review

If strong result:

- Expect 2-3 rounds of review
- Address referee concerns systematically
- Don't overhype (stay conservative in claims)

If null result:

- Emphasize tightest bounds
- Methodological contribution
- Faster review (less contentious)

Month 6-12: Follow-Up Work

Papers in progress:

1. "Scaling Laws for Informational Collapse Bias" (if positive)
2. "Experimental Design for Verrell's Law Validation" (propose dedicated setup)
3. "Meta-Analysis Methods for Quantum Data" (methodology paper)

Experiments proposed:

- If positive: $500K NSF proposal for dedicated interferometer
- If null: Refine Ψμν framework, propose more sensitive tests

Year 2-3: Community Building

Establish working group:

- "Informational Collapse Bias Consortium"
- Coordinate multi-lab efforts
- Standardize protocols
- Annual workshop

Educational outreach:

- Lecture series on Verrell's Law
- Tutorial at APS meeting
- Graduate course module

Final Pre-Flight Checklist

Technical Readiness

- [ ] Python environment set up (3.9+, with scipy, numpy, pandas, pymc3)
- [ ] IBMQ account created and API key saved
- [ ] GitHub repo initialized (public from Day 1)
- [ ] Cloud storage account (AWS/GCP) with billing configured
- [ ] LaTeX environment for manuscript (Overleaf or local)
- [ ] Reference management (Zotero/Mendeley) set up

Administrative Readiness

- [ ] OSF account created (for pre-registration)
- [ ] IRB determination obtained (likely exempt)
- [ ] Data sharing agreement template drafted
- [ ] Email templates prepared (data requests, collaborations)
- [ ] Twitter/X account active for dissemination
- [ ] Personal website updated with project page

Skills Readiness

- [ ] Comfortable with Python data analysis
- [ ] Basic Bayesian statistics (can run PyMC3 models)

- [ ] Version control (git/GitHub proficiency)
- [ ] Scientific writing experience
- [ ] Comfortable with LaTeX or equivalent

Time Commitment

- [ ] 20+ hours/week available for 3 months (minimum)
- [ ] Backup plan if need to extend timeline
- [ ] Collaborator lined up (if solo work not feasible)
- [ ] Supervisor/advisor supportive (if in training position)

The Launch Moment

You are ready to begin when ALL of the following are true:

✓ All checkboxes above ticked
✓ IBMQ account active and API tested
✓ First dataset accessible (even if just IBMQ)
✓ Analysis pipeline coded and tested on synthetic data
✓ Pre-registration drafted (ready to submit)
✓ Next 90 days calendar blocked (realistic time allocation)

The moment to launch: NOW (or Day 1 of allocated time)

Appendix: Email Templates

Template 1: Data Request (First Contact)

```
Subject: Request for historical quantum measurement data (reproducibility study)

Dear Dr. [Name],

I am conducting a pre-registered meta-analysis of quantum measurement time-series
to test for small, reproducible temporal correlations (Verrell's Law / informational
field framework).

Your [YEAR] [EXPERIMENT] published in [JOURNAL] would be invaluable for this study
due to its [SPECIFIC FEATURE: high statistics / controlled environment / etc.].

I am requesting:
- Raw measurement outcomes (individual trials, time-stamped)
- Experimental conditions (temperature, EM environment, detector specs)
- Metadata (measurement protocol, basis choices)
```

```
In return, I will provide:
- Full analysis code (open-source, reproducible)
- Co-authorship if your data represents >5% of total meta-analysis
- Prominent citation and acknowledgment regardless
- Advance access to findings before publication

This work tests the Ψμν informational field tensor framework (attached white paper).
Given your expertise in [THEIR AREA], your dataset would carry particular weight.

Would you be open to sharing? I'm happy to discuss details via video call at your
convenience.

Best regards,
M.R.
Collapse Aware AI Initiative
[email]
[phone]
GitHub: github.com/collapse-aware-ai/verrells-law-archival

Attachments:
- Verrell's Law white paper (15 pages, CC-BY-4.0)
- Pre-registration (OSF link)
- Data sharing agreement template
```

Template 2: Follow-Up (2 weeks after first contact)

```
Subject: Re: Request for historical quantum measurement data

Dear Dr. [Name],

Following up on my email from [DATE] regarding historical quantum data for testing
Verrell's Law.

I understand you may be busy. If sharing the full dataset is not feasible, would
you be open to:
- Sharing a subset (e.g., first 10% of trials)
- Providing aggregate statistics I could compare to my analysis
- A brief call to discuss potential collaboration

Preliminary results from other datasets are [suggestive / null / TBD], and your
experiment would provide valuable [independent confirmation / control / comparison].

No pressure—if timing doesn't work, I completely understand and can follow up at
a later date.
```

```
Best regards,
M.R.
```

Template 3: Thank You (After Receiving Data)

```
Subject: Data received - thank you and next steps

Dear Dr. [Name],

Thank you for sharing the [EXPERIMENT] data! I've received and verified the files
(SHA256: [HASH]).

Next steps:
1. I will process the data using our standardized pipeline (Week of [DATE])
2. Results specific to your dataset will be shared with you privately ([DATE])
3. You'll have 2 weeks to review before we include in combined analysis
4. We'll discuss authorship at that point (if >5% contribution threshold met)

I'll keep you updated on progress and welcome any questions in the meantime.

Again, thank you for supporting open science and fundamental physics research.

Best regards,
M.R.

P.S. If you have any students/postdocs interested in this work, I'd be happy to
share our analysis code and methods as educational resource.
```

Final Word: The Historical Moment

This plan represents the **most achievable path** to testing Verrell's Law:

No new labs needed → Use existing equipment
No new funding needed → Use public data + minimal cloud compute
No permissions needed → Public datasets accessible now
No long timelines needed → 90 days to preprint

The data exists. The signal (if real) is already there, captured inadvertently decades ago.

This is the dark matter moment.

Zwicky saw galaxy rotation anomalies in 1933. Dark matter confirmed 2015 (82 years later).

Aspect, Zeilinger, and others may have captured Verrell's Law signatures in the 1980s-2010s.

We're going to look.

END OF EXECUTABLE 90-DAY PLAN

Status: Ready for immediate implementation

Next action: Day 1, Hour 1 — Access IBMQ database

Repository: https://github.com/collapse-aware-ai/verrells-law-archival

OSF Pre-Registration: [Submit on Day 1]

Contact: [Your details]

"In science, the best discoveries come not from finding new data, but from seeing what's been there all along with fresh eyes."

The hunt begins now.