

Managing Change in Projects:

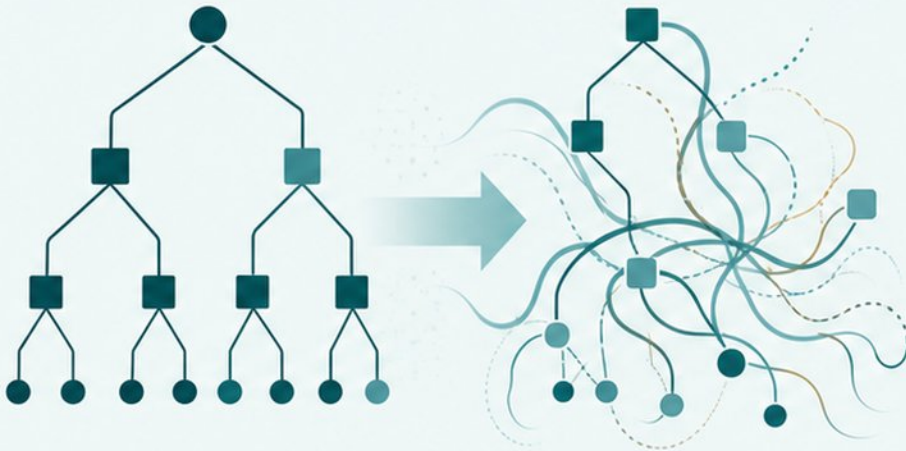
Navigating the Hidden Logic That Shapes Outcomes

- Only 35% of projects succeed;
49% face scope creep
- 52% of projects now hit by
scope creep, up from 43%
- AI introduces data drift,
model updates, and feedback loops
- Governance must span both
traditional scope and AI-driven shifts
- Roadmap: why changes happen ->
governance -> AI-driven suggestions



The Dual Nature of Change: Why Projects and Algorithms Both 'Change Their Mind'

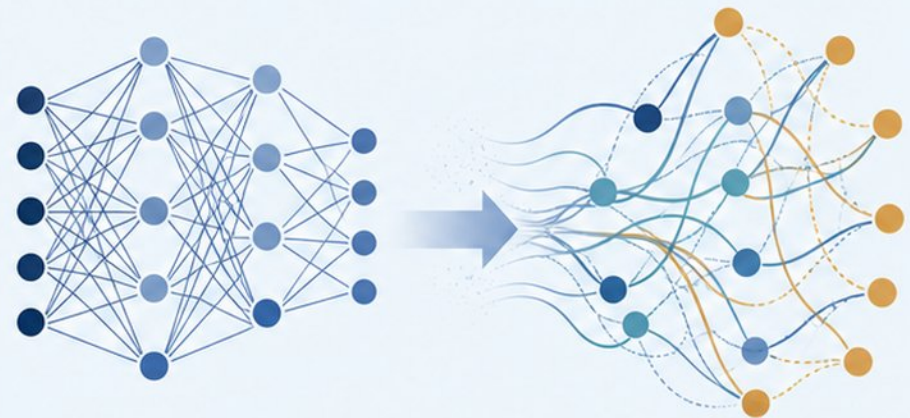
PROJECTS (HUMAN DECISIONS)



Internal drivers: Stakeholder pressure, new requirements, and discovery of unknowns.

External drivers: Market shifts, regulatory changes, and competitor moves.

ALGORITHMS (RECOMMENDATION SYSTEMS)

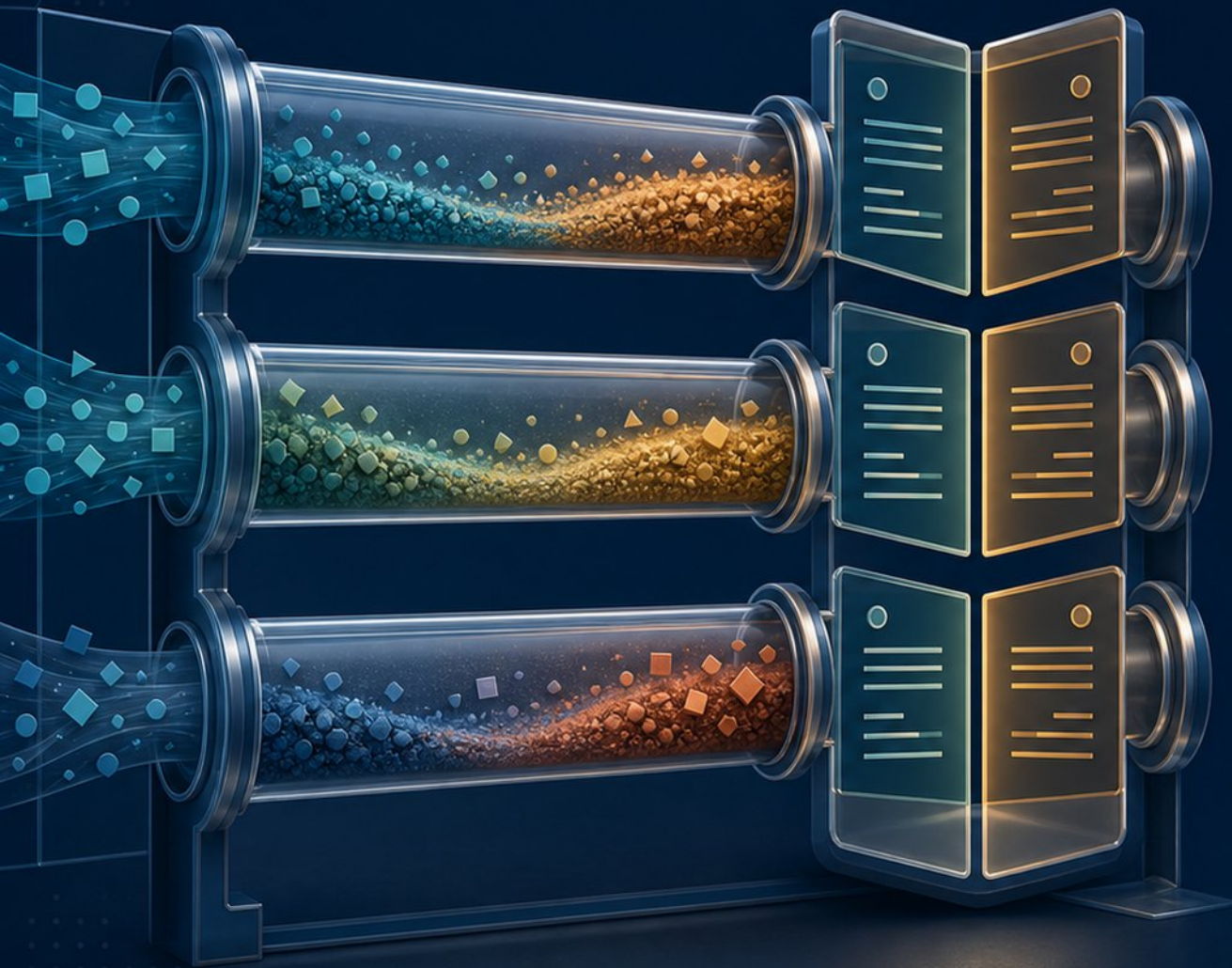


The new dimension: Recommendation systems shift due to data drift, model updates, and A/B testing.



Key bias: We treat machine-generated outcomes as more objective, making their changes feel more disruptive.

Decoding Drift: What 'Change' Looks Like Inside an AI System



- Data Drift: Input data changes; the model sees unfamiliar information, like a store gaining new customer types.
- Concept Drift: The real-world rules change; the same input now means something completely different.
- Model Drift: The system itself changes after technical updates or through self-reinforcing feedback loops.
- Real-world impact: Streaming rankings shift, e-commerce listings shake up, and social feeds change feel.

Traditional Guardrails: Formal Change Control in Project Management



Formal flow:

Change Request → Impact Analysis → CCB Decision → Re-baseline



CCB reviews changes to protect scope, schedule, cost, and quality



Key principles: formal documentation, integrated impact, stakeholder communication



Common failures: undocumented changes, scope creep, and large-IT 'fat tail' risk



A Tale of Two Boards: The CCB Meets the Model Review Board



Both boards ask: **'What changed, why, and what is the impact?'**

- Project CCB: freezes baselines after scope, schedule, cost approvals
- Model Review Board: governs continuously learning, drifting models
- AI governance mirrors project governance (versioning, testing, rollback)
- Your skill: question a recommender change like a scope change request

Thinking Like an AI-Curious Analyst: A 4-Quadrant 'Why' Model



- User Behavior:
shifts in clicks,
intent, or
demographics
(data drift)



- Business Rules:
A/B tests, margin
targets, or
manual overrides



- Item Catalog:
new products,
delisted SKUs,
pricing/availability
changes

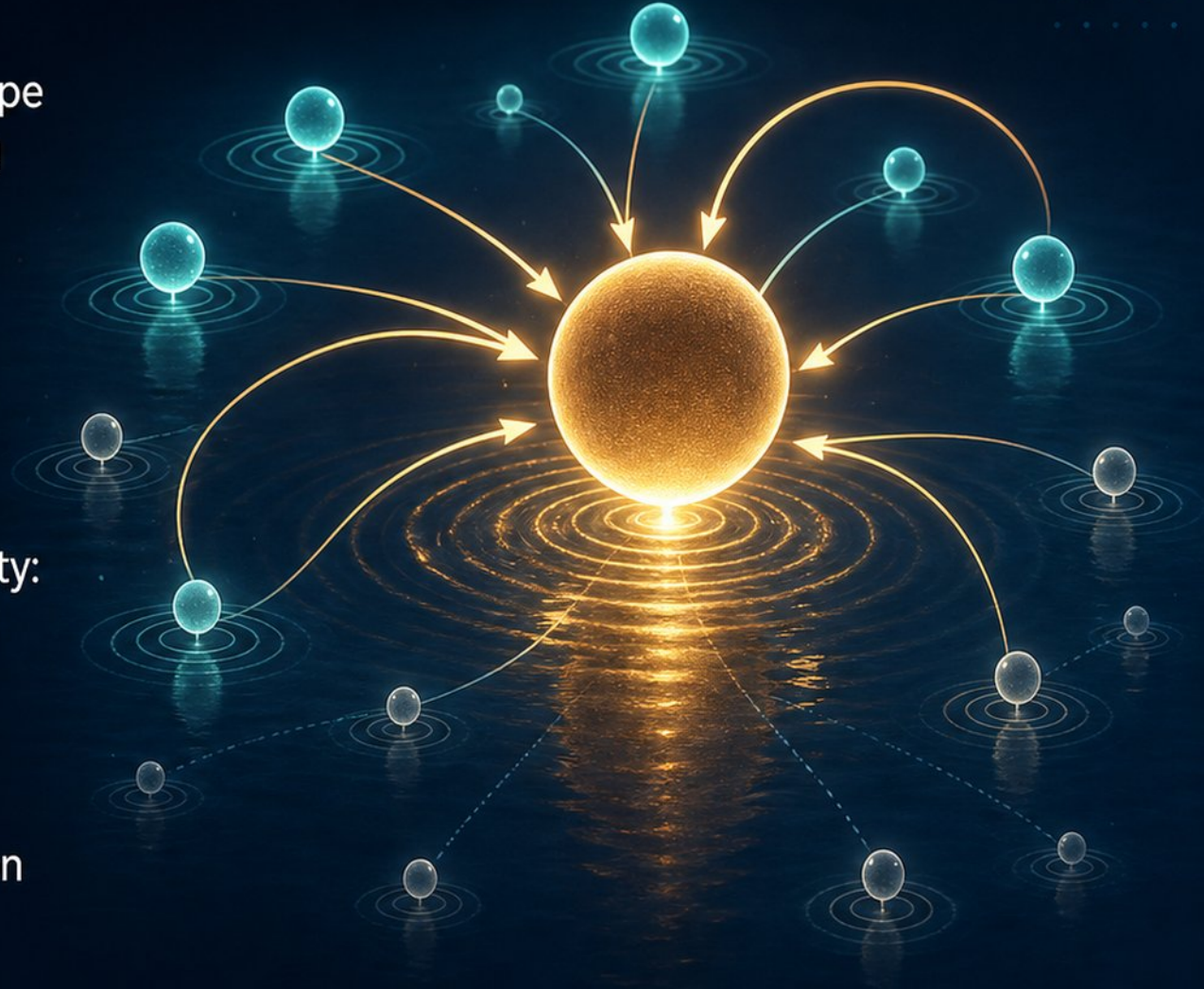


- Model Update:
retrained algorithm,
new signals, or
concept drift



The Invisible Engine: How Feedback Loops and Bias Shape What You See

- "Clicks train models, which shape recommendations, reinforcing what gets popular"
- "Popularity bias creates 'rich-get-richer' dynamics, amplifying top items"
- "Feedback loops reduce diversity: filter bubbles and suppressed niche interests"
- "Optimizing for engagement alone degrades user satisfaction over time"



Anticipating and Governing the Unexpected: Risk, Observability, and AI

- Track AI risk like project scope: use a risk register and contingency reserves.
- Watch for system-specific threats: model degradation, adversarial inputs, and runaway feedback loops.
- Use drift detection as scope trend analysis; monitor data drift, concept drift, and model drift.
- Without observability—monitoring, logging, alerting—AI governance is just guesswork.

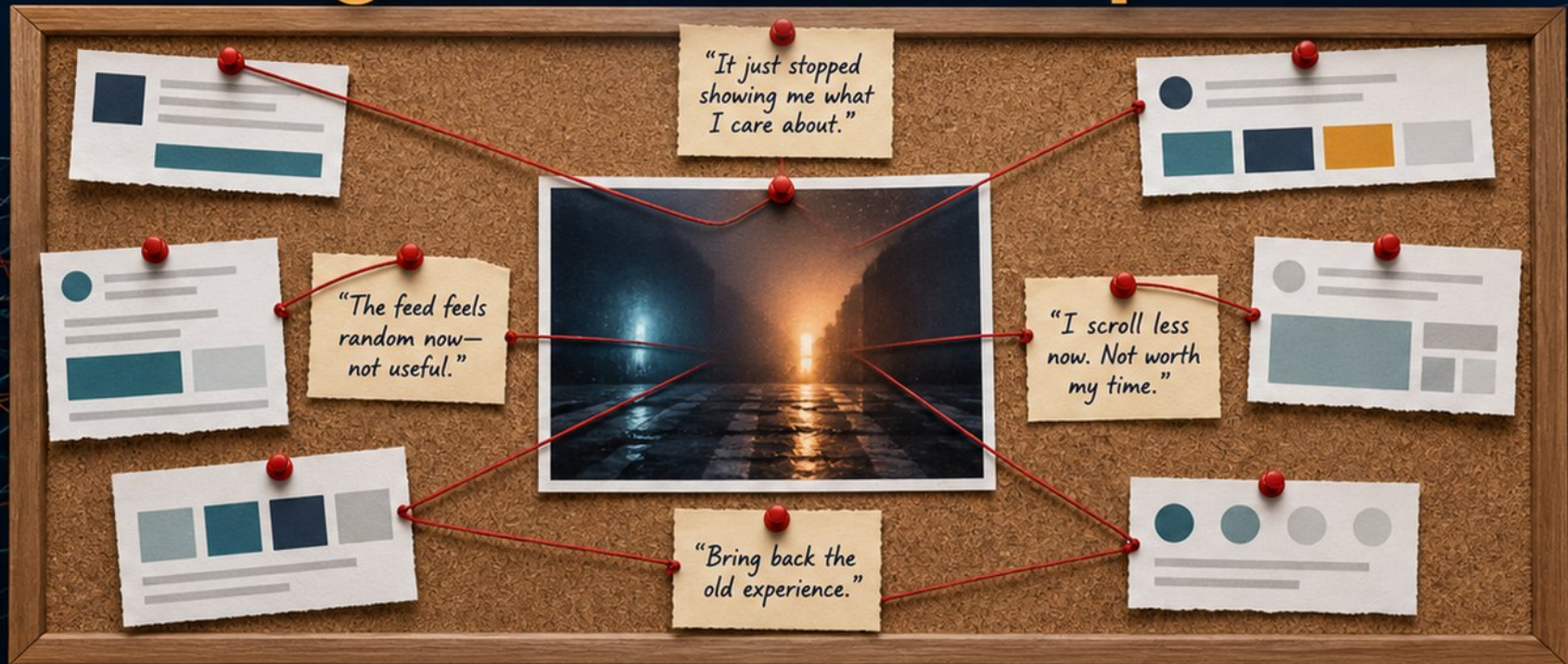


The Human Dimension: From Change Resistance to Change Literacy

- Resistance is often about losing control, not rejecting technology
- AI feels less objective when it acts **on** you rather than **for** you
- Use your levers: feedback tools, preference settings, and transparency dashboards
- Move from 'why did it change?' to 'how can I influence what I see?'



Case Study Deep Dive: When a Model Update Changed a Product Experience



- ▶ - Model retrained → ranking shifted overnight → engagement plummeted, users protested
- ▶ - Timeline: silent launch → traffic anomaly flagged → stakeholder alarm → rollback review
- ▶ - Root cause via 4-Quadrant Model: 'Model Update' quadrant, not user behavior or items
- ▶ - Governance gap: no Model Review Board gate matched to the deployment
- ▶ - Alert signals missed: drift metrics absent, no user feedback loop pre-launch



Practical Strategies: Leading and Tracking Change in Hybrid (Human + AI) Environments



Practical Strategies



- Maintain a Hybrid Change Log: track scope changes and recommender tweaks



- Translate AI output shifts into business impact for stakeholder alignment



- Use a "what changed, why, and what it means" template for all updates



- Build a lightweight dashboard monitoring both project and model KPIs

DUAL-SIDED LEDGER



HUMAN-AUTHORED CHANGE ENTRY



Context, rationale, decisions,
assumptions, next steps



AI-GENERATED VERSION DIFF



Model or data
change detected
by the system



Code, prompt,
or data change
with diff view



Decision impact, stakeholder
update, follow-up actions



Parameter or
logic change
highlighted



Output behavior
change captured
by the model



What it means, impact,
decision, and next steps



Model or data
change detected
by the system



Every change,
explained on
both sides.

✓ What changed?

? Why did it
change?

💡 What does it
mean?

➔ Better context.
Better decisions.
Better outcomes.



Human judgment and AI insight—captured together,
for transparent change management and stronger outcomes.

Your Toolkit: Synthesizing a Unified View of Change and Influence



- Synthesize project scope, AI behavior, and user experience into one governed change surface
- Personal Action Plan: questions, signals, and levers when recommendations shift
- Team Readiness Checklist: align change control with AI governance touchpoints
- Go deeper: AIPGF, ISO 42001, NIST AI RMF, AI Literacy certifications

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