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ENTERPRISE RISK MANAGEMENT: RISING FROM THE ASHES

GEN AI AND

MODEL RISK MANAGEMENT

ROCHAK AGRAWAL

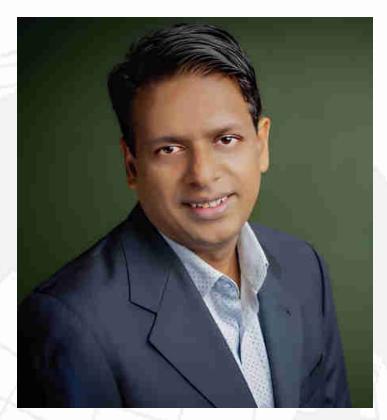
EXECUTIVE DIRECTOR AND HEAD OF RISK

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About the Speaker – Rochak Agrawal



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18+ years of experience in banking technology, risk, and AI innovation.

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Agenda for today (45 mins)

- Why This Matters Now The shift from GenAI pilots to enterprise adoption balancing speed, value, and control.
- Understanding Model Risk in GenAl Failure modes unique to GenAl, and why context amplifies risk.
- Synthetic Data: Benefits, Uses & Testing What it is, practical examples, and how to test for utility, privacy, and bias.
- Build vs Buy (and Blend) Decision Framework Criteria, practical examples, and controls to guide the right choice.
- The Commoditization Curve Where the real value moves as base models become utilities.
- Operating Model & Controls Policies, governance, safety gates, and monitoring for evidence by design.
- 90-Day Action Plan A pragmatic, phased roadmap to go from concept to controlled scale.
- Interactive Scenarios [Audience interactive] Live Build/Buy/Blend exercises to apply the framework.





Why Now: From Pilots to Production

- Embedded already: Service Desk, dev tools, research, reporting, controls testing
- Two pressures: Rapid ROI (from board) and audit-ready evidence of control (from regulator)
- Goal: Measurable value and measurable safety
- Design for scale: Scope, Success, HITL, testing, monitoring from Day 0
- Analogy: Building a highway

"Models are commoditizing; governed integration is the difference"





Model Risk in GenAl

- Model risk: Harmful/incorrect/non-compliant outcomes from Al
- GenAl failure modes: Hallucination, privacy leakage, jailbreaks, bias/toxicity
- Risk amplifiers: Long context, Long memory ,tool use, autonomy, feedback loops
- Context matters:
 - Separate "cause" from "context"
 - Safe in sandbox ≠ safe in production
- Analogy: Very Fast, Very Helpful intern you still review outputs!





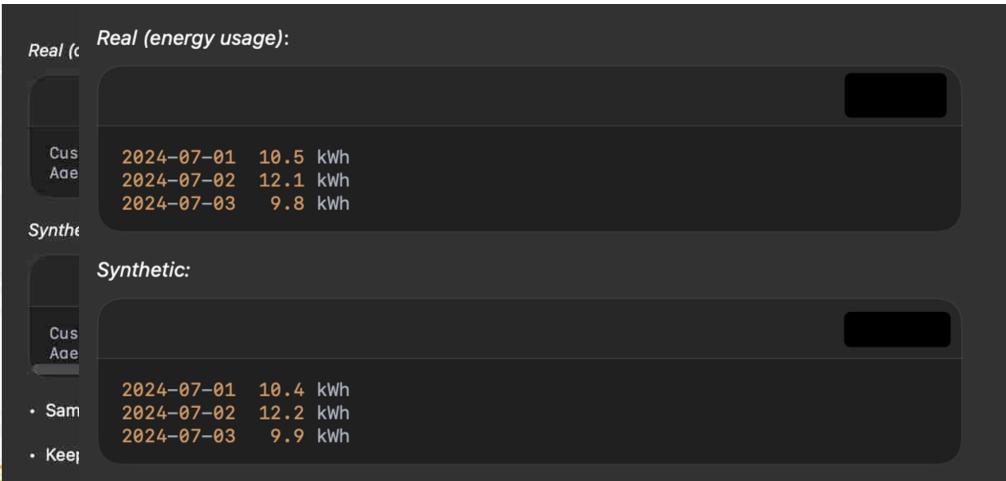
Synthetic Data 101: What, Why, Types

- Definition: Artificially generated data that mimics real distributions
- Why use it: Privacy-by-design, rare-case coverage, balancing speed
- Common types: Tabular/time-series, text/dialogue, images/docs, logs
- Key caveat: Fidelity ≠ truth; bias can persist or amplify.
- Analogy: It's a shield not a cloak





Model Risk in GenAl







Synthetic Data: Risks & Utility Tests

Risks:

- Privacy risk: Memorisation of real records.
- Bias preservation/amplification: Skewed patterns remain or worsen.
- Low fidelity: Unrealistic patterns that don't match production.
- Utility overestimation: Adds noise, lowering real-world performance.

Utility & Safety Tests:

- Downstream performance comparison: Real vs Real+Synthetic. Calculate F1 score.
- Rare-class coverage: Match or slightly oversample important low-frequency cases.
- Drift & robustness tests: Check stability under changing patterns.
- Membership inference: Detect leakage of real records.
- Nearest-neighbor distance: Ensure synthetic ≠ direct copy of real records.

Analogy: think of synthetic data as a shield, not a cloak





Recap Template: Synthetic Data Test Plan

- 1. Objective & scope of synthetic dataset
- 2. Utility metrics: downstream accuracy, rare-class lift
- 3. Privacy tests: membership inference, NN distance
- 4. Bias/fairness evaluation plan
- 5. Governance artifacts: dataset card, lineage, risk scores
- 6. Acceptance criteria & sign-off



GenAl Models: The Commoditization Curve

- Base models → utility: Rapid releases, lower cost
- Value shifts up-stack: Data, retrieval, guardrails, workflows
- Design for swap-ability: Orchestration layers
- Winning pattern: Thin customization + thick governance + deep integration
- Engine -> Base Model
 Fuel -> Your data
 Brakes and Seatbelts -> Your guardrails
 Driver Training -> Your operating model





Internal vs Third-Party Models: Clear Trade-offs

- Internal/open-weight: Pros (control, transparency, cost), Cons (ops burden, talent). Think: Training your own models using ML studio (not foundation models)
- Hosted/API: Pros (quality, speed, safety), Cons (lock-in, data risk, explainability). Think: Azure hosted OpenAI models, License, Vendor solutions
- Middle Hybrid path: RAG + adapters, secure gateways, contractual clauses "No train". Think: hosted models but internal RAG layers (embeddings, data filters).





Build vs Buy Decision Matrix

- Criteria: Strategic fit, Data advantage, Risk constraints, Time/talent, TCO, Vendor terms
 - Is it core IP/differentiating? If yes → bias to Build/Adapt.
 - Do we have a data advantage? If yes → Build/Adapt to exploit it.
 - Are there hard constraints? Residency, explainability → Self-host/Open-weight.
 - Do we need results in weeks? If yes → Buy to start; design portability.
 - What is true TCO? Include evals, safety, monitoring, updates, staffing, switching.
 - Can we exit? Demand no-train, deletion SLAs, export, pricing caps/ramps.
- Scoring: 1–5 scale for each criterion
- Weighting: Assign importance per org strategy
- Total score: Guide decision (Build / Buy / Blend)





- Policies: Al use, model risk, data handling, HITL
- Governance: Model Inventory, Risk tiering, approvals, validation (second line)
- Safety: Evaluation suites, jailbreak tests, red-team logs
- Monitoring: Logs, alerts, incident mgmt
- Operating Model: Al Steering Committee, Model Risk Committee, Deliver Pods, RACI
- **Controls**: Contractual (no-train on prompts/outputs), deletion SLAs, architectural, assurance, monitoring, change mgmt





How to start: 90-Day Plan

90-day plan:

- 0–30 days pick use cases (high –ROI) and establish policy baselines
- 31–60 days build RAG pipeline, implement safety gates, pilot with HIL
- 61–90 days scale & validate, negotiate no-train contracts, setup independent validation





AUDIENCE Turn



Scenario 1: Summarising 2M Historic Customer Emails



- Goal: "We need an AI to summarise 2 million historic customer emails for training a support bot. Build, Buy, or Blend?"
- Options: Build, Buy, or Blend?
- Consider privacy, speed, and compliance





Answer: Blend

- Hosted LLM for language summarisation quality and speed
- PII scrubbing before sending data outside
- In-house RAG layer retrieves only masked, relevant excerpts [e.g next slide]
- Meets privacy & compliance while delivering quickly





Masked Email → Embedding → Vector DB

- Original email: Dear support, my account 123456 was double charged for product X on Jan 5.
- **Step 1:** Masked email: Dear support, my account [ACCOUNT_NUMBER] was double charged for product X on Jan 5.
- **Step 2:** Generate embedding (vector representation of meaning) using openweight model (e.g., SentenceTransformers).
 - Example vector (truncated): [0.021, -0.143, 0.532, 0.287, ...] for Step 1
- **Step 3 :** Store embedding + metadata (date, product, issue type, masked text) in secure vector DB (e.g., Milvus, Weaviate, Pinecone).





Retrieval → Prompt → Safe Summary

- Step 1: Query: 'All refund-related complaints in January 2023'
- Step 2: Vector DB converts query to embedding and retrieves most similar masked chunks.
 - Retrieved examples:
 - 1. Dear support, my account [ACCOUNT_NUMBER] was double charged for product X on Jan 5.
 - 2. I was charged twice for my subscription in Jan.
- Step 3: Prompt to hosted LLM: Summarise key themes; exclude personal identifiers.
- **Step 4:** LLM output: Multiple customers experienced double charges in early January. Issues affect both purchases and subscriptions. Customers request immediate refunds.





Scenario 2: Fraud Detection Synthetic Data

- Goal: "We need a GenAI to generate fake transaction histories for fraud detection model training. Build, Buy, or Blend?"
- Options: Build, Buy, or Blend?
- Consider domain specificity and privacy





Answer: Build

- Fraud patterns are highly domain-specific
- Full control over generation rules and validation
- Run privacy tests: membership inference, re-identification
- Hosted options may lack transparency for sensitive data





Scenario 3: Developer Copilot

- Goal: "We want a coding assistant for internal devs. Build, Buy, or Blend?"
- Options: Build, Buy, or Blend?
- Consider speed, quality, and IP protection





Answer: **Buy first**

- Hosted LLMs trained on massive codebases deliver quality fast
- Add repo scoping and secrets filters
- Measure test pass-rate & defect reduction
- Evaluate open-weight build later for cost and IP control



Scenario 4: Customer Complaint Classification

- Goal: "We need to classify incoming customer complaints into risk categories in real time. Build, Buy, or Blend?"
- Options: Build, Buy, or Blend?
- Consider internal data sensitivity and user experience





Answer: Build

- Classification can be a smaller model fine-tuned on your proprietary labelled data. lightweight to run in-house with minimal latency.
- Gives full control and explainability for compliance/audit (important in risk categorisation).
- Hosted may be overkill and risk exposing sensitive complaint content.





Scenario 5: HR Policy Q&A Bot

- Goal: "We need a chatbot for employees to query HR policies, benefits, and procedures. Build, Buy, or Blend?"
- Options: Build, Buy, or Blend?
- Consider internal data sensitivity and user experience





Answer: Blend

- Hosted LLM for natural conversation
- In-house RAG for secure HR document retrieval
- Only safe excerpts sent externally
- Delivers quality while safeguarding sensitive info







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THANK YOU

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