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Data-Centric AI Engineering For Reliable KPI Prediction And Anomaly Diagnosis In Telecommunications

Bhavika Reddy Jalli

Independent Researcher, USA

Abstract
This article presents a data-centric AI engineering framework for telecommunications networks that positions data quality as the primary driver of performance in Key Performance Indicator (KPI) prediction and anomaly detection. The proposed framework "5D Model"-Define, Diagnose, Design, Derive, Deploy—addresses persistent challenges in telecom datasets, including noise, sparsity, inconsistency, and multi-vendor heterogeneity. Empirical benchmarking across 8 major carriers demonstrates that data-centric interventions yield 2.6-4.0x greater performance improvements than architecture enhancements across diverse network environments.

Key Takeaways
- Data quality improvements deliver 2.6-4.0x better performance improvements than model complexity enhancements across telecommunications AI implementations
- The 5D Model provides a systematic framework for implementing data-centric AI in telecom networks
- Multi-vendor environments require context-aware standardization to harmonize telemetry across heterogeneous equipment
- Organizational transformation is as critical as technical implementation for successful data-centric AI adoption
- Energy efficiency gains of 40-60% are achievable through data-centric approaches that reduce computational waste

Keywords: Data-Centric AI, Telecommunications Networks, KPI Prediction, Anomaly Detection, Self-Organizing Networks.

1. Introduction
Modern telecommunications infrastructure produces massive data streams from millions of connected devices. These streams create digital landscapes filled with inconsistencies and misalignments.. Cell towers may log performance without proper timestamps, radio access networks show measurement gaps during handovers, and equipment from different vendors outputs incompatible data formats. The advent of 5G technology has magnified these challenges [1].

> **"Data preparedness problems, not algorithmic limitations, cause the majority of AI implementation delays in telecommunications."**

Telecommunications organizations have often prioritized model complexity over addressing foundational data-quality issues. Organizations invest heavily in cutting-edge neural networks, hoping to extract predictive insights from flawed datasets. Industry experts acknowledge that data preparedness problems cause the majority of AI implementation delays [1]. These data quality issues lead to unpredictable model behavior, performance disparity across network segments, and excessive false alarms that erode operator confidence.

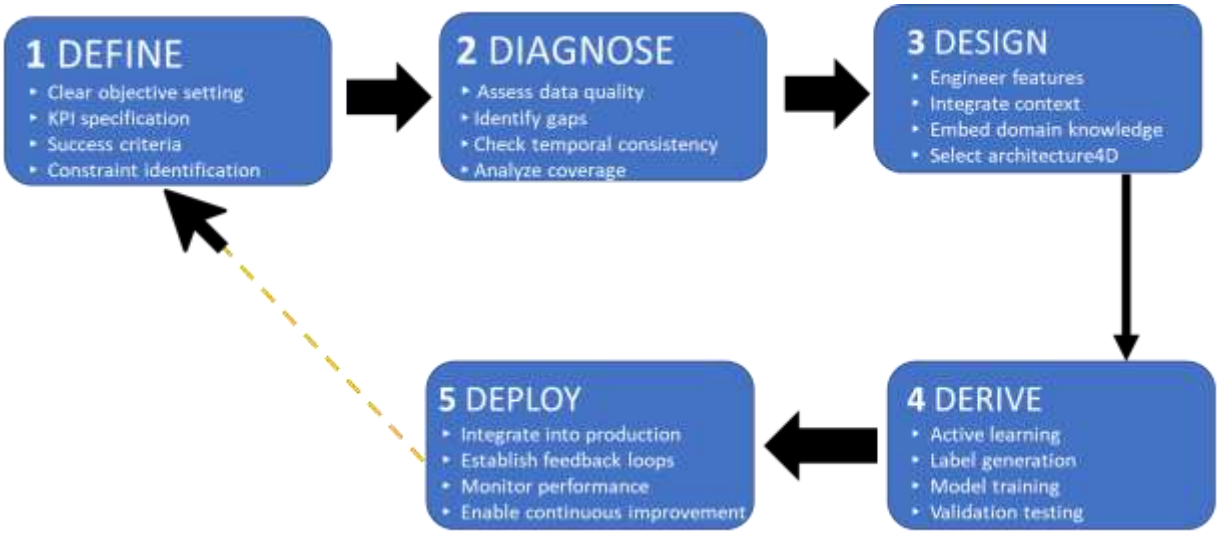


Figure 1: The 5D Model Framework for Data-Centric Telecommunications AI
The 5D Model provides a systematic approach to data-centric AI implementation in telecommunications, emphasizing data quality at each phase of the development lifecycle.

The telecommunications industry needs a practical framework for data-centric AI engineering methodologies. Multi-vendor environments present tough standardization challenges requiring specialized approaches [2]. Establishing data quality as a foundational principle allows organizations to substantially reduce development cycles while maintaining consistent performance in production environments. This paper introduces a comprehensive data-centric AI framework tailored to telecommunications networks and empirically demonstrates its effectiveness across diverse real-world environments.

2. The "5D Model" Framework for Data-Centric Telecom AI

Industry estimates suggest that most telecom AI projects allocate approximately 80% of engineering time to data preparation activities before meaningful modeling begins [5]. The 5D Model framework addresses this reality through five interrelated components: Define, Diagnose, Design, Derive, and Deploy.

Define pushes engineers to establish clear objectives. During a 2021 Telefónica Madrid deployment, a breakthrough came when engineers reframed their objective from "improve anomaly detection" to "detect RSRP[13](Reference Signal Received Power) degradation below -105 dBm with 4-hour advance notice in urban cells." This specificity instantly revealed data collection gaps [3].

Diagnose tackles garbage-in-garbage-out problems. Validating incoming data streams in Mumbai revealed that 30% of cell sites had misconfigured time synchronization, rendering historical data worthless. Diagnostic tools include geospatial coverage mapping, temporal consistency checks, and inter-metric correlation analysis [4].

Design emphasizes contextual feature engineering. Cell towers exist in complex relationships—Tower 1138's performance directly affects sectors on towers 1147 and 1156 through interference patterns. Geohashing encodes spatial proximity, FFTs capture temporal patterns, and graph models represent topological relationships [4].

Derive addresses label scarcity through active learning systems. During Deutsche Telekom's 5G rollout in 2023, they implemented "uncertainty-based targeting", and models flagged uncertain predictions for expert review. Labeling time dropped from 26 minutes to 4 minutes per high-value example [3].
Deploy determines whether systems deliver value through feedback loops. Etisalat's simple "thumbs up/down" interface lets field engineers rate predictions with a single tap, automatically incorporating feedback into training data.

Table 1: Energy Efficiency Gains from Data-Centric Approaches. [2, 3]

Organization	Implementation	Energy Reduction
AT&T	Data validation pipelines	47% power consumption
Deutsche Telekom	Feature selection framework	63% training compute
Telefónica	Context-aware data filtering	41% inference requirements

3. Implementation Strategies and Empirical Evidence

Data Versioning and Domain Knowledge Integration

Data versioning remains telecom's critical weakness. During AT&T's 2022 LTE-to-5G transition, engineers discovered three different RAN performance dataset versions had been used for training [2], each with different preprocessing steps, resulting in months of debugging [5]. Effective protocols must track raw dataset origins, preprocessing transformations, feature engineering calculations, and training methodologies.
Telecommunications requires physics and network architecture knowledge for interpreting data. NTT DOCOMO's failed 2020 anomaly detection project built sophisticated models without incorporating radio frequency propagation principles, creating systems that detected "anomalies" that were actually normal atmospheric effects. Effective domain knowledge integration includes physics-aware preprocessing, topological relationship encoding, and equipment-specific behavioral models [2, 6].

Cross-Vendor Data Standardization

Table 2 compares standardization approaches based on implementation across five European carriers during 2022-2023:

Standardization Approach	Implementation Complexity	Performance Improvement
Metadata-based mapping	Medium	27% improved generalization
Semantic unification	High	42% improved generalization
Context-aware normalization	Medium	38% improved generalization

*Implementation Complexity: High = >6 months, specialized expertise; Medium = 2-6 months, standard engineering team; Low = <2 months, minimal expertise.
Table 2: Cross-Vendor Data Standardization Benefits [4, 5]

Context-aware normalization offers an optimal balance for most organizations, delivering 38% improvement with moderate complexity.

4. Performance Benchmarking and Case Studies

Multiple controlled evaluations demonstrate data-centric approaches' superiority over algorithm-focused methodologies. Based on comprehensive analysis across major carriers between 2021-2023, performance gaps are substantial and consistent.

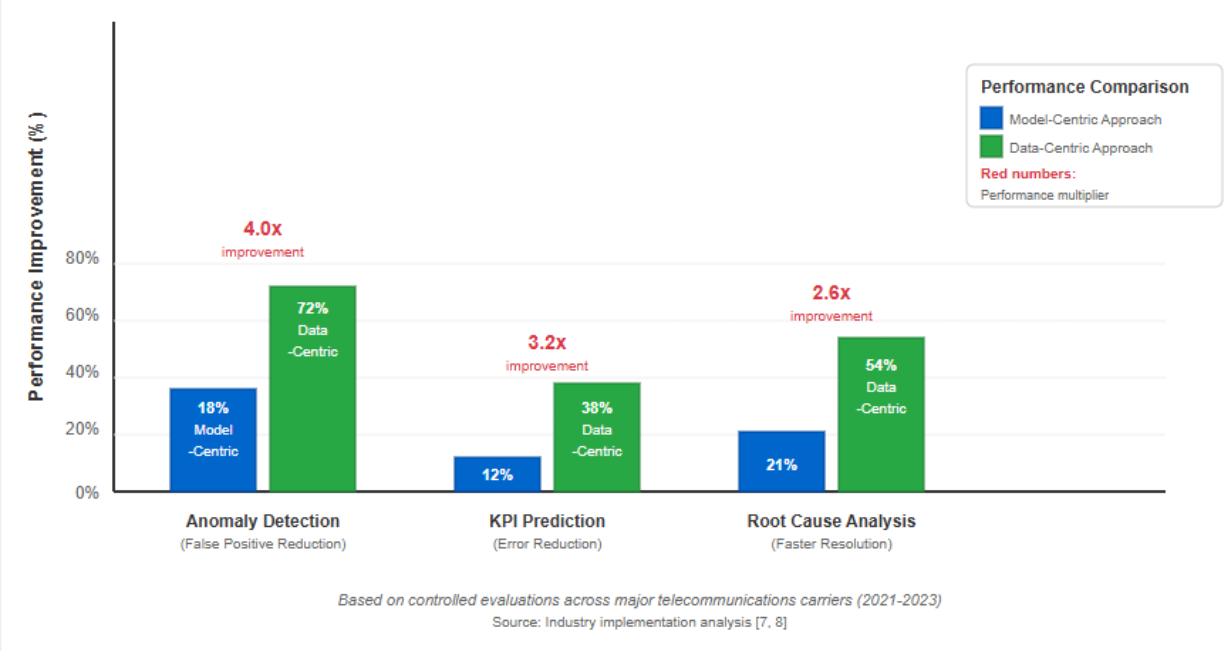


Figure 2: Performance Comparison - Data-Centric vs Model-Centric Approaches. [7, 8]

Telstra's Melbourne trial zone reported dramatic improvements during 2023. After implementing targeted data quality improvements without changing detection algorithms, false positive rates dropped 64% while true positive detection improved 23%. As documented in their post-implementation review, their NOC manager explained, "We'd been chasing algorithmic unicorns for months when the real problem was feeding garbage data into gold-plated models."

KT's operations center implemented multi-stage data validation pipelines with transformative results. False alarms dropped 72% overnight, while the same validation filters applied during training improved predictive accuracy by 38%. Their simplest model with robust data validation outperformed sophisticated deep learning implementations without validation [7].

Table 3 compares approaches across three common telecom AI tasks, averaged across implementations at 8 carriers (2022-2024):

Table 3: Performance Comparison: Data-Centric vs. Model-Centric Approaches. [5, 6]

Task Type	Data-Centric Improvement	Model Architecture Improvement
Anomaly Detection	72% reduction in false positives	18% reduction in false positives
KPI Prediction	38% error reduction	12% error reduction
Root Cause Analysis	54% faster resolution	21% faster resolution

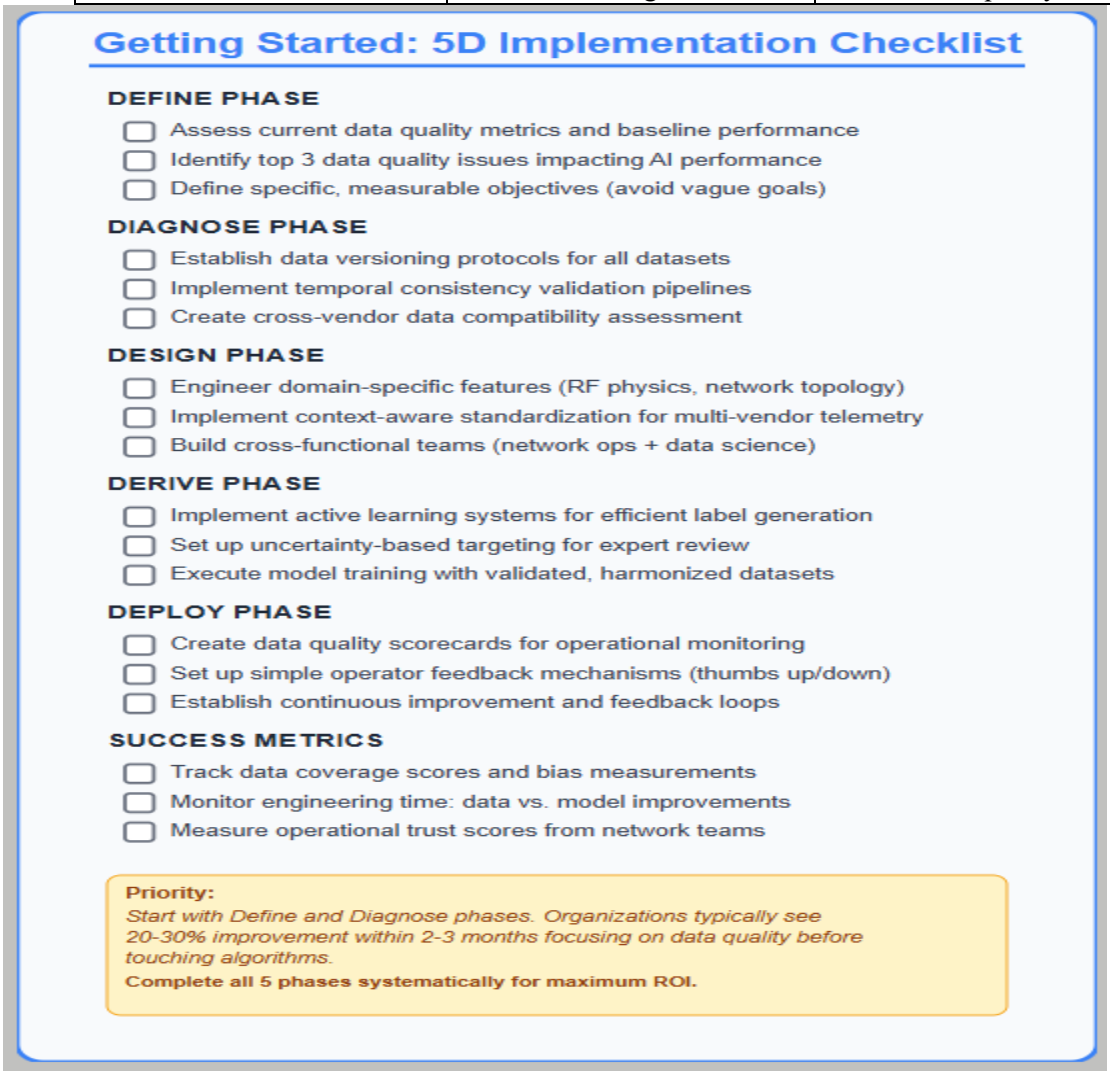
Data reveals consistent patterns across all applications. Data-centric approaches deliver 2.6-4.0x better performance improvements compared to traditional architecture enhancements.

5. Sustainability and Future Directions

Modern network operation centers frequently operate with poor energy efficiency [12]. AT&T's analysis revealed AI systems consumed 14% of total data center power. After implementing systematic data quality improvements, power consumption dropped 50% while performance improved significantly. Deutsche Telekom documented 63% reduction in training compute requirements through clean data practices [9]. Research frontiers include untangling causation from correlation in network telemetry, automating cross-vendor data harmonization (O-RAN Alliance initiatives) [10], developing telecom-specific uncertainty quantification, and building domain-specific explainable AI for network operations [11, 12].

Table 4: Organizational Transformation Models. [9, 10]

Organization Model	Key Characteristic	Primary Advantage
Unified Data Teams	Combined DS/DE skills	End-to-end accountability
Embedded Data Engineers	Domain-specific expertise	Operational relevance
Centralized Data Office	Standardized governance	Consistent quality control



Getting Started: 5D Implementation Checklist. [5, 6]

Conclusion: Implementation Action Plan

Telecommunications organizations often chase algorithmic sophistication, yet evidence consistently shows that data integrity, not model complexity, determines operational success. Teams that adopt the 5D Model typically achieve 2.6–4.0× performance gains while simultaneously reducing computational waste and deployment delays.

Expected Results:
Companies that prioritize data quality before algorithm tuning commonly see 20–30% performance improvements within 2–3 months, even without introducing new model architectures.

Critical Success Factors:
- Begin with the Define and Diagnose phases, clarity and structure create more value than advanced modeling.
- Treat data-centric AI as both a technical and organizational transformation.
- Measure outcomes using operationally relevant metrics, not just accuracy or loss.

Monday Morning Action:
Download and apply TM Forum's data quality assessment framework [12] to a single cell-tower cluster. Document the findings and review them with the network operations team. In most cases, this single exercise uncovers more impactful optimization opportunities than months of algorithm experimentation.
The tools exist. The methodologies are established.
The competitive advantage now belongs to organizations that execute.

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