Universal Library of Innovative Research and Studies | Research Article

ISSN: 3065-0003 | Volume 3, Issue 3

Open Access | PP: 32-36

DOI: https://doi.org/10.70315/uloap.ulirs.2026.0303006

Bridging Technical Telemetry and Business Decision-Making through Data Product Management

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Abstract

Enterprise leaders rely on telemetry from digital platforms, yet operational metrics, incident records, logs, traces, and service signals often remain detached from managerial work. Technical teams use these signals for diagnosis, while executives need evidence that explains customer impact, operational risk, cost exposure, and prioritization trade-offs. The article examines how data product management turns telemetry into trusted decision input for enterprise operations. The study develops an analytical model that connects observability signals, shared metric definitions, governance controls, ownership, and feedback routines. The method combines qualitative source analysis, comparative review, typologization, and conceptual synthesis of ten recent academic and industry sources on data products, observability, Business Intelligence and Analytics (BI&A) success, data governance, analytics capability, and Connected Intelligence. The analytical section identifies three results: telemetry needs product boundaries before it enters management routines, trust depends on semantic discipline and ownership, and decision value increases when feedback links business outcomes with system behavior. The proposed model supports Monthly Business Reviews, SRE analytics, operational intelligence programs, and enterprise data functions.

Keywords: *Data Product Management, Technical Telemetry, Operational Intelligence, Observability, Business Intelligence, Decision-Making, Site Reliability Engineering (SRE) Analytics, Data Governance, Metric Standardization, Connected Intelligence.*

INTRODUCTION

Digital enterprises generate dense telemetry from applications, infrastructure, user behavior, incidents, service health, business workflows, and automated decision systems. Signal scarcity rarely blocks managerial work. Friction begins when those signals remain inside engineering tools, local dashboards, incident logs, or team-specific metric definitions. Executives then receive delayed, inconsistent, or excessively technical versions of operational reality. Reliability teams face a parallel difficulty: they can diagnose system behavior, yet they struggle to show how service performance affects revenue, user trust, productivity, and strategic execution (Li et al., 2022; Blohm et al., 2024; Bernardo et al., 2024; Ul Ain et al., 2025; Hurbean et al., 2023).

The article aims to develop an analytical framework explaining how data product management connects technical telemetry with business decision-making in large organizations. The first research objective clarifies how technical telemetry becomes decision-ready after teams treat it as a governed data product. The second objective determines which trust mechanisms help engineering and business teams use shared metrics without semantic conflict. The third objective explains how feedback loops connect telemetry, business outcomes, and recurring management routines.

The novelty of the article lies in the managerial translation of operational signals. The study does not reduce the subject to broad data governance. It treats telemetry as input into decisions about resilience, customer experience, cost, capacity, prioritization, and strategic risk. The proposed hypothesis states that technical telemetry supports business decision-making only after product managers and domain teams connect ownership, shared definitions, quality controls, and feedback mechanisms with measurable business outcomes.

MATERIALS AND METHODS

The literature search covered Scopus-indexed journals, SpringerLink, ScienceDirect, Taylor & Francis, PubMed Central, ResearchGate records used only for bibliographic verification, and publicly available industry publications. Search strings combined "data product", "data mesh", "observability", "microservice tracing", "business intelligence success", "analytics capability", "data governance quality", "decision-making performance", "SRE telemetry", and "operational intelligence". The initial pool contained 46

Citation: Sushrutha Sreevathsa, "Bridging Technical Telemetry and Business Decision-Making through Data Product Management", Universal Library of Innovative Research and Studies, 2026; 3(3): 32-36. DOI: https://doi.org/10.70315/uloap.ulirs.2026.0303006.

potentially relevant records. Screening used title and abstract fit, publication venue, recency, methodological clarity, and alignment with the decision-centered focus of the article. The review excluded 36 records because they were outside the required period, relied on promotional claims, appeared in weak outlets, focused on narrow algorithmic testing, or discussed governance without a decision workflow. The final corpus contains ten sources: conceptual work on data products, data mesh, and data fabric, an industrial survey of observability practices, systematic or review-based work on data governance and BI&A success, empirical studies on BI&A adoption and decision-making performance, a product management paper on data use, a general data analytics review, a case study on analytical capabilities, and an industry chapter on Connected Intelligence.

The study applies comparative source analysis, conceptual synthesis, typologization, and analytical generalization. Comparative analysis links telemetry studies with BI&A and product-management literature. Conceptual synthesis builds the bridge between observability signals and managerial decision logic. Typologization separates raw telemetry, curated operational indicators, decision-ready metrics, and feedback-enabled data products. Analytical generalization forms a non-experimental model suitable for academic discussion and enterprise implementation.

RESULTS

The literature reveals a persistent gap between data availability and decision usability. General data science research describes analytics as a process that converts diverse data into knowledge for decision-making, but this broad formulation does not fully resolve the enterprise telemetry problem because reliability signals rarely reach managers in a usable form (Sarker, 2021). A Central Processing Unit (CPU) saturation pattern, error budget burn, latency spike, or incident recurrence gains managerial meaning only after teams connect it with user impact, service dependency, operational cost, customer friction, or risk exposure. The first result concerns the status of telemetry itself: raw technical signals do not function as managerial evidence until teams assign product boundaries, semantic meaning, quality expectations, and a defined consumer.

Research on data products, data mesh, and data fabric explains this conversion with greater precision. Data products operate as socio-technical units designed for repeated consumption, discoverability, ownership, and standardized use across domains (Blohm et al., 2024). For telemetry, this approach changes the treatment of operational data. Engineering systems may generate the signal, but the organization needs a product contract around that signal: meaning, owner, freshness requirement, decision link, reliability test, and known limitation. A technical dashboard can remain accurate inside engineering practice while producing unstable evidence for business reviews if teams lack that contract.

Observability research sharpens the same point. Industrial work on microservice tracing shows that traces, metrics, and logs serve different diagnostic needs, and engineering teams benefit when they interpret service behavior across distributed systems (Li et al., 2022). SRE and platform teams use this interpretation for diagnosis. Business leaders need a different consumption layer. The same signal has to explain degraded checkout flow, delayed content delivery, lower advertising quality, support burden, productivity loss, or operational risk. The source signal remains technical. Its decision use depends on translation. Data product management supplies that layer by defining the telemetry consumer, decision path, quality threshold, and escalation rule.

The second result concerns trust. Data governance research emphasizes quality management, stewardship, accountability, maturity models, and organizational controls as conditions for extracting value from enterprise data (Bernardo et al., 2024). In telemetry work, trust extends beyond access and compliance. It depends on metric standardization across engineering and business teams. A “critical incident”, “availability loss”, “degraded experience”, “active user impact”, or “service recovery” metric loses managerial value when separate teams calculate it through incompatible rules. In operational intelligence, the governance problem starts with shared meaning before it reaches procedure.

BI&A success literature reaches a related conclusion from another route. A recent review reports that BI&A success is often measured through ease of use, information accuracy, financial performance, system features, presentation quality, and decision-making performance, while the decision-performance dimension receives less attention than enterprise practice requires (Ain et al., 2025). This finding has direct relevance for telemetry analytics because many operational dashboards receive evaluation through technical completeness or visual quality. A telemetry data product requires a stricter success test. A management meeting, incident review, capacity decision, or product prioritization process should change because the signal reached the forum in a trusted, timely, and interpretable form.

Empirical work on BI&A adoption adds the organizational layer. Studies of BI&A adoption connect analytics with managerial work performance and decision effectiveness, with data-driven culture functioning as an enabling condition (Hurbean et al., 2023). A separate case study of analytical capabilities identifies barriers linked to systems, management, personnel capability, weak goals, difficulties proving benefits, communication gaps, and fragmented cooperation between business units (Teittinen & Bovellan, 2023). These findings explain why telemetry projects often lose force after dashboard launch. The technical artifact exists, but the organization has not specified the user, decision, and route through which evidence moves from an engineering surface into a management routine.

The Connected Intelligence frame develops this reasoning further. The published industry chapter on enterprise data and AI argues that value depends on alignment among data, models, governance, humans, and decision workflows more than on model sophistication alone (Sreevathsa, 2026). The implication for this article is narrower than the original framework. Telemetry becomes useful when it participates in a continuous system where decisions feed learning back into the data product. In Monthly Business Review practice, reliability signals, anomaly patterns, operational bottlenecks, and customer-impact indicators should enter review cycles as governed decision inputs with owners, thresholds, and follow-up actions. Figure 1 summarizes the analytical distribution of recurring telemetry-to-decision dimensions identified across the reviewed literature. The visualization groups the dominant themes discussed in studies on observability, BI&A systems, data governance, operational intelligence, and data product management (Ain et al., 2025; Bernardo et al., 2024; Blohm et al., 2024; Li et al., 2022; Sreevathsa, 2026).

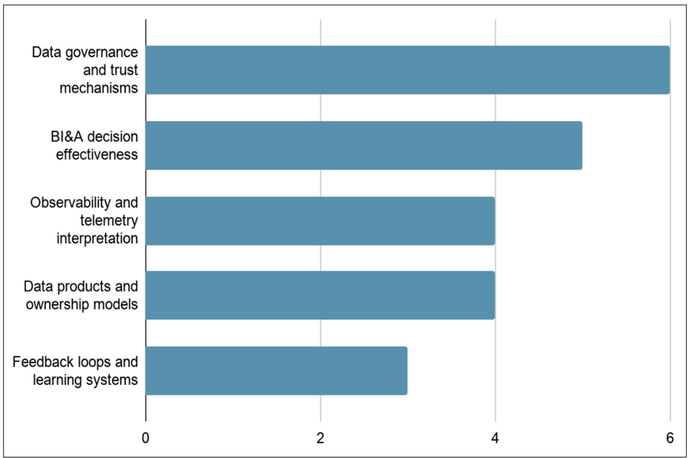

Figure 1. Analytical distribution of telemetry-to-decision dimensions in the reviewed literature (compiled by the author based on Ain et al., 2025; Bernardo et al., 2024; Blohm et al., 2024; Li et al., 2022; Sreevathsa, 2026)

The reviewed literature concentrates most heavily on governance consistency, metric trust, and decision effectiveness. Fewer studies examine feedback integration between telemetry systems and management routines, despite its operational relevance for Monthly Business Reviews, escalation management, and reliability planning. The distribution highlights a structural imbalance in the current literature. Researchers devote greater attention to infrastructure, governance, and analytics architecture than to the managerial reuse of telemetry inside recurring decision processes.

Four strands of literature support this claim when read together. Observability research concentrates on distributed system diagnosis through technical signals and analytical workflows (Li et al., 2022). Data product research moves attention toward reusable, consumer-oriented, governed data assets (Blohm et al., 2024). BI&A success literature tests whether analytics systems improve decision outcomes, usability, and performance (Ain et al., 2025). The Connected Intelligence model links data, models, people, governance, and feedback into a continuous operating environment (Sreevathsa, 2026). Together, these positions indicate that telemetry passes through three translations before it influences management: from system behavior to operational meaning, from operational meaning to business relevance, and from business relevance to accountable action.

Product management research adds another rationale for this translation. Recent work on product management success factors highlights growing dependence on data analytics for strategic decision-making and product steering (Fichtler et al., 2025). In telemetry-based decision systems, the data product manager translates operational signals into management priorities. This function differs from ordinary reporting ownership. It requires decisions about which signals deserve executive visibility, which metrics belong in recurring reviews, which thresholds require action, and which interpretations should be excluded because they are noisy, duplicated, or detached from decisions.

A separate cluster of studies focuses on capability formation inside analytics-driven organizations. Research on business analytics capability and decision-making performance indicates that data literacy skills and knowledge management mediate the relationship between data-driven culture and analytics capability (Fattah et al., 2025). In operational intelligence, the bridge between telemetry and decisions depends on human interpretive capacity. Leaders need enough literacy to understand what telemetry can prove and where it has limits. Engineers need enough business fluency to connect reliability signals with customer, revenue, productivity, and risk consequences. Data product managers work at this boundary and turn telemetry into a shared language for action.

DISCUSSION

The proposed position treats technical telemetry as a decision asset after productization. The distinction matters because many organizations equate visibility with intelligence. Visibility means that a system produced signals and placed them in front of users. Intelligence begins after teams curate those signals, test their quality, assign ownership, connect them with business meaning, and place them inside a decision routine. A strong operational dashboard without a metric owner, semantic contract, and action pathway remains fragile. Engineers may use it for diagnosis, while leadership may still lack evidence for prioritization.

The implementation model begins with decision inventory. The organization identifies recurring decisions where telemetry has practical value: service reliability funding, incident prevention, roadmap sequencing, capacity planning, vendor evaluation, technical debt prioritization, customer-experience remediation, and operational risk review. Each decision receives a narrow set of telemetry-derived indicators. Selection should remain strict. A metric belongs in the product when it changes a decision, accelerates escalation, reduces ambiguity, or improves accountability.

Metric standardization follows. Technical teams often maintain precise local definitions, while business forums need stable comparability across domains. A telemetry data product therefore needs a metric dictionary, calculation logic, source lineage, freshness rule, confidence status, and known limitations. Metric governance should avoid slow approval queues. It should function as a trust layer inside the product lifecycle. A definition dispute should trigger product review because disagreement over meaning damages decision quality more than a delayed visualization update. Table 1 compares telemetry as a monitoring artifact with telemetry as a managed data product. The purpose is to show how data product management changes the organizational status of technical signals.

Table 1. Comparison of telemetry artifacts and telemetry data products (compiled by the author based on Ain et al., 2025; Blohm et al., 2024; Li et al., 2022; Sreevathsa, 2026)

Comparison criterion	Telemetry as monitoring artifact	Telemetry as data product
Primary consumer	Engineers and incident responders	Engineers, product leaders, operations managers, executives
Main function	Detect, diagnose, and troubleshoot system behavior	Support decisions about reliability, risk, investment, and customer impact
Definition logic	Tool-specific or team-specific	Shared semantic contract
Ownership	Platform, SRE, or service team	Named product owner with domain participation
Quality expectation	Signal availability and diagnostic detail	Accuracy, freshness, lineage, interpretability, business relevance
Review cycle	Incident response and technical retrospectives	MBRs, operational reviews, planning forums, performance governance
Success measure	Faster diagnosis and technical visibility	Better prioritization, reduced ambiguity, improved decision accountability
Feedback mechanism	Alerts, postmortems, observability tuning	Decision outcomes, action tracking, metric recalibration

The comparison shows that data product management extends SRE practice. Technical teams still need granular logs, traces, and metrics for diagnosis. Management forums need stable interpretation and decision linkage. A shared telemetry base can serve both uses if the product layer separates raw diagnostic depth from curated decision signals. Table 2 presents a practical maturity sequence for implementation. It fits organizations that already maintain telemetry and analytics tools but lack a reliable bridge into business routines.

Table 2. Maturity sequence for telemetry-to-decision data product management (compiled by the author based on Bernardo et al., 2024; Fattah et al., 2025; Fichtler et al., 2025; Teittinen & Bovellan, 2023)

Maturity level	Organizational condition	Product-management action	Evidence of progress
Fragmented signals	Metrics differ across tools and teams	Identify repeated decision problems and remove unused signals	Smaller metric set with clearer purpose
Curated indicators	Reliability and operational signals are visible but weakly standardized	Define metric contracts, owners, freshness rules, and lineage	Fewer disputes over definitions
Decision-ready products	Indicators are mapped to business outcomes	Connect telemetry to MBRs, incident economics, customer impact, and roadmap choices	Metrics appear in decisions, not only dashboards
Governed operating rhythm	Metric definitions, quality checks, and ownership are embedded in routines	Establish review cadence, escalation logic, and exception handling	Faster action on threshold breaches
Learning system	Decisions generate feedback into telemetry products	Recalibrate thresholds, retire weak metrics, add missing signals	Improved relevance of operational evidence over time

The maturity sequence avoids the premise of a broad transformation launched before evidence of use. A narrow telemetry data product can begin with one recurring decision, for example, whether a reliability initiative deserves roadmap priority. The product team selects a limited number of service signals, connects them with business impact, defines quality thresholds, and tests whether leadership can make a clearer decision. Scaling should follow proven use, not dashboard completion.

Monitoring metrics for such a program should cover technical and managerial performance. Technical measures include freshness, completeness, lineage coverage, incident linkage, anomaly detection quality, and metric calculation stability. Managerial measures include decision adoption, the number of MBR decisions supported by telemetry products, fewer unresolved metric disputes, action closure rate, recurrence of previously addressed incidents, and time from signal detection to accountable action. Dashboard traffic offers weak evidence. A stronger indicator is whether a decision changed and whether the organization can trace the reason for that change.

The proposed approach has limits. Telemetry can overrepresent what teams can measure and underrepresent qualitative causes such as leadership disagreement, market pressure, user perception, or organizational fatigue. Productizing telemetry does not remove judgment. It disciplines the evidence that enters judgment. A second limit concerns metric gaming. Once telemetry-derived indicators enter leadership routines, teams may optimize visible thresholds while hidden failure modes persist. Periodic metric review, rotating qualitative checks, and post-action validation reduce this risk.

Implementation should follow a controlled sequence. The team selects one high-value decision, identifies the telemetry signals behind it, defines the product owner, standardizes terms, documents lineage, sets freshness and confidence rules, embeds the product into a recurring decision forum, captures action outcomes, and revises the product after use. This sequence keeps the organization from building a broad operational intelligence layer before a smaller data product proves that it can improve a decision.

CONCLUSION

Technical telemetry gains managerial value when teams transform raw system output into a governed data product with explicit ownership, shared definitions, quality rules, and a defined decision consumer. Logs, traces, events, incidents, and reliability metrics support leadership after teams connect their operational meaning with user impact, cost, risk, service continuity, and prioritization.

Trust in telemetry-based decision-making depends on semantic discipline. Metric standardization, lineage, freshness, documented limitations, and cross-functional ownership reduce the distance between engineering interpretation and executive review. Without these mechanisms, dashboards multiply while decisions remain contested.

Feedback loops complete the bridge between telemetry and business action. Recurring forums such as Monthly Business Reviews should treat telemetry products as living decision assets. Their value becomes visible when decisions, post-action outcomes, and revised assumptions feed product improvement. The hypothesis is confirmed: technical telemetry supports business decision-making when product management connects signal quality, shared meaning, governance, and decision accountability into one operating rhythm.

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