International Journal of Advances in Data and Information Systems
Vol. 7, No. 1, April 2026, pp. 202~216
ISSN: 2721-3056, DOI: 10.59395/ijadis.v7i1.1503

Data Analytics Capability Maturity and Governance Gaps in PT ABC: A Diagnostic Case Study

Almon Junior Simanjuntak[1], Achmad Nizar Hidayanto[2], Raden Trimanadi[3,4]
[1,2,3]Faculty of Computer Science, Universitas Indonesia, Indonesia
[4]Faculty of Computer Science, Universitas Esa Unggul, Indonesia

Article Info

Article history:
Received Dec 27, 2025
Revised Jan 14, 2026
Accepted Jan 20, 2026

Keywords:
Data Analytics Capability
Data Analytics Maturity
STDAMM
Data Governance
Maturity Model

ABSTRACT

This study provides a within-case diagnosis of data analytics capability maturity in PT ABC to inform refinement of its 2025 to 2026 governance roadmap. Using a qualitative-first mixed-method diagnostic case design (QUAL→QUAN), this study conducted five semi-structured key-informant interviews first, followed by a cross-sectional survey of 76 purposively selected analytics-involved employees, analyzed using the Shortened TDWI Data Analytics Maturity Model (STDAMM). The overall maturity mean was 3.31 on a 5-point scale (bootstrap 95% confidence interval: 3.15 to 3.46), classifying the assessed respondent pool as Level 3 (Established). Dimension means were tightly clustered (3.27 to 3.35) with substantial confidence-interval overlap, suggesting that respondents perceive maturity as a coupled system rather than sharply separated capability domains. A small descriptive pattern placesanalytics use and infrastructure marginally above data management and organizational enablement, consistent with interview accounts of definition inconsistency, limited socialization of dictionary and stewardship practices, and recurring manual reconciliation of figures across systems. The findings support a governance-first refinement of the roadmap that prioritizes standardization and ownership mechanisms to improve the comparability and decision-readiness of analytics outputs, while treating subgroup comparisons cautiously where measurement comparability is not supported.

This is an open-access article under the CC BY-SA license.

Corresponding Author:
Almon Junior Simanjuntak,
Faculty of Computer Science,
Universitas Indonesia,
Jl. Lingkar, Pondok Cina, Depok, West Java 16424, Indonesia.
Email: almon.junior@ui.ac.id

1. INTRODUCTION

In Indonesia's fast-growing digital economy, organizations are increasingly expected to shift from intuition-based decision-making to developing systematic Enterprise Data Management (EDM) capabilities [1], [2]. This change is significant for State-Owned Enterprises (SOEs) after the recent creation of the Danantara Investment Management Agency and the introduction of the "Melayani Sepenuh Hati" mandate, which focuses on responsive and measurable public service standards [3], [4]. For PT ABC, operating in the competitive fields of courier, logistics, and non-bank financial services [5], failing to manage data effectively may exacerbate operational risk and weaken competitiveness amid market liberalization.

Although PT ABC has responded by developing the 2025–2026 Data and Information Governance Transformation Roadmap [6], a gap remains between strategic intent and operational execution. This gap is evidenced in the 2025 IT governance assessment using COBIT 2019, which reported a low score for the Managed Data objective (Align, Plan, Organize/APO14) at 2.07 [7], alongside weak institutionalization signals at the practice level, such as business glossary

standardization (APO14.02) and data quality strategy (APO14.04) (see Table 1). The internal assessment covered multiple COBIT objectives; APO14 is highlighted here because managed-data discipline is directly implicated in analytics comparability and reuse across units. In COBIT 2019, Governance and Management Objectives (GAMO) APO14 is decomposed into 10 management practices (APO14.01–APO14.10) and 59 underlying activities, indicating that "managed data" requires more than policy articulation and depends on consistent execution across a broad set of practices and activities [8]. These baseline indicators are presented to frame the starting point for the study and to motivate the within-case diagnostic analysis reported in the subsequent sections.

Table 1. Excerpt of internal COBIT 2019 APO14 assessment results

Practice Code	Practice Name	# of Activities	Maturity Score	As-is Indication
APO14.02	Define and maintain a consistent business glossary	6	2.05	The central glossary is not yet institutionalized as the reporting/system reference.
APO14.03	Establish the processes and infrastructure for metadata management	10	2.05	Metadata exists in several systems, but lacks a centralized repository/metamodel.
APO14.04	Define a data quality strategy	6	2.05	Data-quality efforts exist but are not consolidated into a corporate strategy with clear targets/metrics.
Overall	**Data management governance baseline**	**59**	**2.07**	**Assessment result indicates a managed but not yet standardized enterprise routine.**

However, governance assessments have limitations. COBIT 2019-based diagnostics can surface structural and control gaps, but may not fully capture how analytics is used in day-to-day decision processes or whether capability shortfalls reflect limited adoption versus informal, locally managed analytics practices outside standardized governance mechanisms [8]. Therefore, a governance-only audit is insufficient to locate how analytics capability is experienced in routine reporting and decision processes. This study profiles analytics capability maturity using the STDAMM survey and derives its empirical interpretation through within-case triangulation with interview accounts. The COBIT APO14 result is presented as contextual starting-point evidence for managed-data practice institutionalization, not as a parallel measurement stream.

This study contributes to the literature by addressing limited evidence on integrated data analytics capability assessments in SOEs that operate under public-service accountability while competing commercially [10], [11]. While prior studies in Indonesia have often examined governance readiness and analytics capability separately [12], this study provides a within-case analytics maturity assessment at PT ABC using STDAMM [13] and uses qualitative triangulation to translate the maturity profile into implementable roadmap implications.

To guide the refinement of the 2025–2026 roadmap, this research addresses two specific questions:

RQ1. What is the current maturity level of PT ABC's data analytics capabilities?

RQ2. Which areas of data analytics capability should be prioritized to close the gap between the current state and the company's transformation targets?

2. THEORETICAL BASIS

2.1. Enterprise Data Management and IT Governance

To effectively manage data as a strategic asset, organizations rely on Enterprise Data Management (EDM), which integrates data governance, data management, and data analytics [14], [15], [16]. While data analytics focuses on deriving insights, it relies heavily on the foundations set by data governance (policies/standards) and data management (technical execution/quality) [14], [17]. Without these foundations, analytics initiatives often suffer from "garbage in, garbage out" scenarios [18].

In the context of execution, IT Governance provides the structure to align these data assets with organizational goals [19], [20]. The COBIT 2019 framework operationalizes IT governance through governance and management objectives, including APO14 (Managed Data), which

specifies practices such as data strategy, business glossary discipline, metadata management, and data quality direction [8].

2.2. Data Analytics and Maturity Models

Data analytics transforms managed data into decision-relevant insight and commonly evolves through four stages: descriptive, diagnostic, predictive, and prescriptive analytics [1], [21]. In organizational settings where data governance and reporting practices are still consolidating, maturity assessment provides a structured way to describe the current capability state and to identify improvement priorities rather than to claim progress over time [9], [22].

In this paper, the term "diagnostic" is used in two related but distinct senses. First, a maturity model can be diagnostic as a framework for assessing capability and guiding improvement. Second, a survey instrument can be diagnostic as a measurement scale that enables statistical evidence checks (for example, reliability and construct-level screening) to support cautious interpretation of maturity scores in a new organizational context. These two senses are compatible, but they lead to different model requirements depending on the study design and evidence goals.

Accordingly, the maturity model selected for this study is expected to (i) provide a transparent survey-based measurement instrument suitable for academic replication, (ii) have prior empirical validation, and (iii) operationalize maturity as a measurement scale that supports reliability testing and dimension-level gap diagnosis [9], [22]. Table 2 summarizes that several widely cited practitioner-oriented maturity models are useful for organizational self-assessment workshops but are less suitable for replicable survey research because their instruments are not publicly accessible or their empirical validation is limited. For example, the TDWI Analytics Maturity Model has limited instrument access and lacks reported empirical validation for replication purposes (Model 1) [23]. The Delta Plus Model provides neither accessible documentation nor an instrument (Model 2) [27]. APMM is documented but does not provide an available instrument and reported validation for this study's use case (Model 3) [28]. DAMAF is also constrained by limited documentation and instrument availability (Model 5) [30].

Table 2. Maturity Model in the Data Analytics area

Model	Maturity Stage	Focus	Origin	Documentation?	Instrument?	Empirical Validation?	Model Type
(1)	5 level	Organization Analytic Programs	Practitioner	V	n.a	X	Measurement scale
(2)	5 level	Organization Analytic Implementation	Practitioner	X	X	n.a	Maturity Grid
(3)	5 level	Organization Analytic Process	Academia	V	X	X	n.a
(4)	6 level	Data Science	Academia	V	V	V	Measurement scale
(5)	6 level	Data Analytics Maturity	Academia	X	X	n.a	n.a
(6)	4 level	Advanced Data Analytic Capabilities	Academia	V	V	V	Maturity Grid
(7)	5 level	Data Analytics Maturity	Academia	V	V	V	Measurement scale

Note: V: Yes; X: No; n.a: Limited access or information

(1) TDWI Analytics Maturity Model [23], **(2)** Delta Plus Model [27], **(3)** APMM [28], **(4)** DSCMM [29], **(5)** DAMAF [30], **(6)** ADA-CMM [31], **(7)** STDAMM [13]

Academically developed models can provide stronger measurement foundations, but they differ in how maturity is operationalized. DSCMM was considered because it is documented, instrumented, and empirically validated; however, it operationalizes maturity with a primary focus on data science capability (Model 4) [29]. ADA-CMM is empirically validated and suitable for structured diagnosis of "advanced analytics capability," yet it operationalizes maturity as a maturity grid with fewer levels and scenario-based descriptors (Model 6) [31]. This design is well-suited for qualitative benchmarking and case-based diagnosis, but it offers less flexibility for psychometric screening and dimension-level statistical analyses that this paper uses to address measurement concerns in a cross-sectional survey setting.

By contrast, the STDAMM is documented, provides an accessible measurement instrument, and is empirically validated (Model 7) [13]. Because STDAMM operationalizes maturity as a multi-dimensional measurement scale, it supports statistical diagnostics that complement internal-consistency evidence and help bound interpretation when applying the instrument in a new organizational context. Therefore, STDAMM is used in this study as the primary quantitative instrument to quantify perceived analytics maturity and support within-case diagnosis and prioritization. The empirical interpretation is based on triangulating STDAMM patterns with within-case interview evidence.

2.3. Previous Case Studies and Research Gap

The application of maturity models in the Indonesian context has grown, yet distinct gaps remain. As summarized in Table 3, the majority of recent case studies (2017 to 2025) focus on Data Governance or Master Data Management, commonly using governance-centric reference frameworks such as DAMA-DMBOK [10], [11], [24]. While studies on Big Data and Data Warehousing also exist [12], [25], they predominantly target government agencies or selected private-sector contexts, which limits transferability to multi-business SOEs that must coordinate standards, controls, and reporting across heterogeneous operational units.

Table 3. Previous Maturity Model Case Study in Indonesia

Case Study	Sector	Research Focus	Maturity Model
Dinas Parpora [32]	Government	Data Management	DAMA-DMBOK framework [15]
Government Org in the Financial sector [33]	Government	Business Intelligence (BI)	Business Intelligence Maturity Model (BIMM)
STIE XYZ, Pasuruan, Jawa Timur [34]	Education	Process Capability Model	COBIT 5 Domain MEA01 [8]
Diskominfo Kota Sukabumi [35]	Government	Data Governance	Stanford Data Governance Maturity
PT ABC (Fintech P2P Syariah) [36]	Private	Data Governance	IBM Data Governance Maturity Model
PT Graha Segara [11]	Private	Master Data Management	Master Data Management Maturity Model (MD3M) [9]
National Narcotics Board (BNN) [25]	Government	Data warehouse	Data Warehouse Capability Maturity Model (DWCMM)
Direktorat Jenderal Pajak [37]	Government	Advanced Analytics/CRM	Analytic Process Maturity Model (APMM) [28]
Sekretariat Dewan Pertimbangan Presiden [38]	Government	Master Data Management	Master Data Management Maturity Model (MD3M) [9]
Arsip Nasional Republik Indonesia [24]	Government	Data Governance	Stanford DG Maturity Model
PT. XYZ [39]	Private	Big Data Adoption	TDWI Big Data Maturity Model [23]
Badan Pusat Statistik (BPS) [40]	Government	Master Data Management	Master Data Management Maturity Model (MD3M) [9]
Direktorat Jenderal Bea & Cukai [12]	Government	Big Data	TDWI Big Data Maturity Model [23]
Mahkamah Agung (Supreme Court) [41]	Government	Master Data Management	Master Data Management Maturity Model (MD3M) [9]
PT. Telkomsel [42]	Private	Data Quality	Data Quality Framework, DMBOK [15], and Big Data Quality Assessment

A second gap is that many published cases treat governance readiness and analytics capability maturity as separate diagnostic streams. To bridge this gap, the study integrates an STDAMM-based maturity profile with interview-based within-case triangulation to translate survey signals into roadmap implications.

3. RESEARCH METHOD

3.1. Research Design

This study adopts a sequential mixed-method diagnostic case study (Qualitative→Quantitative). In this design, interview evidence functions as the interpretive lens for explaining STDAMM results. Consistent with the dual-diagnostic framing established in Section

2.2, semi-structured interviews were conducted first to inform interpretation of the subsequent survey patterns and translate quantified gaps into actionable roadmap priorities.

Given the internal distribution and cross-sectional nature of the instrument, the quantitative evidence is interpreted as perception-based indicators rather than audit-grade measures. To reduce extreme satisficing risk and clarify evidentiary strength, the analysis plan incorporates response-pattern screening for long-string straight-lining [43], robustness checks using sensitivity comparisons between raw and cleaned means, and complementary measurement diagnostics beyond Cronbach's alpha, including composite reliability and average variance extracted (CR and AVE) [44]. Discriminant validity is screened using the heterotrait-monotrait ratio of correlations (HTMT) [45]. To bound the interpretation of HQ and Branch subgroup contrasts, measurement comparability was screened using the Measurement Invariance of Composite Models (MICOM) procedure [46], and subgroup results are reported descriptively when comparability is not supported. Uncertainty around key descriptive estimates is summarized using nonparametric bootstrap confidence intervals [47], [48]. Accordingly, the study does not make causal claims or estimate change over time; findings are intended for within-case diagnosis and analytic transfer to similar organizational settings.

3.2. Population and Sample

This study used purposive nonprobability sampling to reach employees who routinely consume, produce, or govern analytics outputs (e.g., report owners, analysts, data stewards/data governance-related roles, and decision-makers). Accordingly, the intended population for inference is not the entire PT ABC workforce, but rather the subset of employees directly involved in analytics routines and data governance practices.

As shown in Table 4, the realized respondent pool is skewed toward mid-to-top management (76.3%) and slightly head-office leaning (52.6%). This composition provides a strategically informed view of perceived maturity among analytics stakeholders. Still, it may under-represent hands-on operational frictions typically experienced in branch/regional workflows (e.g., frontline reporting, data entry, and local reconciliation practices). Therefore, the survey results should be interpreted as perceptions within this purposive respondent pool, rather than as organization-wide estimates of maturity.

Table 4. Respondents by Organizational Position (cleaned N=76)

Category	Person	%
A. Position		
SVP/EVP	2	2.6
VP/Deputy VP	8	10.5
EGM/OGM/DEGM/DOGM	7	9.2
Senior Manager/Manager/Assistant Manager/Supervisor	41	53.9
Functional staff	18	23.7
Total	76	100
B. Office (Work Unit)		
Head Office	40	52.6
Main/Branch Offices	27	35.5
Regional Offices	9	11.8
Total	76	100
C. Tenure in the Company		
< 2 years	4	5.3
2–5 years	4	5.3
5–10 years	14	18.4
> 10 years	54	71.1
Total	76	100

3.3. Variable Operationalization

To measure data analytics maturity, this study adopted the STDAMM developed by Ioakeimidou et al [13]. The instrument comprised 24 items measured on a 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree), grouped into five dimensions:

- Organization (ORG): Leadership sponsorship, culture, and strategy alignment.

- Infrastructure (INF): Tools, skills, and technological adaptability.
- Data Management (DMAN): Integration, analysis breadth, and ERP usage.
- Analytics (ANL): Team structure, advanced techniques, and decision impact.
- Governance (GOV): Policies, ownership, retention, and security.

Item responses were aggregated as mean scores at the overall scale and dimension level. For reporting clarity, the overall mean is mapped to five maturity labels using pre-specified score bands on the 1–5 Likert scale (band width = 0.80): Level 1 = 1.00–1.80, Level 2 = 1.81–2.60, Level 3 = 2.61–3.40, Level 4 = 3.41–4.20, and Level 5 = 4.21–5.00. In the roadmap analysis, Level 4 (Mature) is operationalized as an aspirational benchmark (target score = 4.00) to express a gap-to-target view, not as an audit threshold (see Section 4.4 and Table 15).

3.4. Data Collection and Analysis Method

Data collection proceeded in two phases consistent with a qualitative-first sequence. First, a qualitative component was conducted to anchor the study in observable reporting, analytics, and governance routines. Semi-structured interviews were carried out with five purposively selected key stakeholders (R01-R05) to capture both strategic and tactical perspectives before the survey was distributed.

The informants comprised two Vice Presidents (R04 - VP Digital Giro and Payment Solution, R05 - VP Courier Operation), two Managers (R01 - Manager Giro Services Management, R02 - Manager Reporting and Data Analytics), and one Assistant Manager (R03 - Assistant Manager IT Service Management), each with more than 10 years of experience. Purposive selection emphasized functional coverage across business and technology support functions and direct involvement in analytics-related reporting and data governance activities rather than representativeness of the broader workforce. An interview guide ensured consistent coverage across informants, focusing on: (i) decision contexts requiring analytics outputs, (ii) data-definition and master-data consistency issues, (iii) reconciliation practices when figures conflict across systems, and (iv) the extent and consistency of formal governance mechanisms (e.g., dictionary, stewardship, escalation). Interviews were audio-recorded with participant consent and transcribed verbatim.

Interview transcripts were analyzed using iterative thematic coding to identify recurring operational patterns relevant to the governance-gap diagnosis. For integration, the resulting themes were aligned to the same five STDAMM dimensions reported in the survey results to support transparent within-case triangulation when interpreting the maturity profile. Given the targeted key-informant design (N=5), the qualitative component is used for within-case diagnostic explanation rather than saturation-driven theory building; accordingly, no formal inter-coder reliability statistics are reported.

Second, a point-in-time online questionnaire was administered for 15 days via internal management communication channels to capture respondent-reported maturity among employees involved in analytics routines. The survey used the STDAMM instrument described in Section 3.3. Quantitative data analysis followed a prespecified diagnostic workflow. First, data integrity and response-quality checks documented item completeness and screened for extreme response patterns (e.g., long-string straight-lining) to reduce the risk of careless responding. Second, internal consistency was assessed using Cronbach's alpha as an exploratory reliability screen. Third, complementary measurement diagnostics were computed at the construct level, including Composite Reliability and Average Variance Extracted (CR and AVE) and discriminant validity screening using the Heterotrait-Monotrait ratio (HTMT). Fourth, measurement comparability between HQ and Branch was screened using the Measurement Invariance of Composite Models (MICOM) procedure to bound subgroup interpretation. Fifth, descriptive maturity estimates were summarized using means and dispersion, and uncertainty in key mean estimates was reported using nonparametric bootstrap confidence intervals (CI). Sixth, a nonparametric profile screen was conducted to assess within-respondent differences across the five dimensions (Friedman test), with Kendall's W reported as an effect-size indicator. Finally, a gap-to-target view compared observed

maturity means against the Level 4 (Mature) benchmark used in the organization's roadmap as an aspirational reference for prioritization.

4. RESULTS AND DISCUSSION

4.1. Data Quality, Reliability, and Robustness Check

To improve response quality and reduce straight-lining bias, a data-cleaning process was applied to 81 submissions. No item-level missing responses or duplicates were found (Table 5). Exclusions were limited to response-pattern screening: a long-string analysis identified five respondents who answered identically on all 24 items, indicating straight-lining patterns [43]. These cases were excluded, resulting in a final sample of N=76.

Table 5. Response quality diagnostics (long-string analysis)

Metric	Value
Total respondents (initial dataset)	81
Number of Likert items per respondent	24
Duplicate submissions	0
Item missingness	0
Minimum longest run of identical answers	2
Median longest run of identical answers	7
Maximum longest run of identical answers	24
Respondents with the longest run = 24	5
– all answers = "Setuju"	2
– all answers = "Sangat setuju"	2
– all answers = "Tidak setuju"	1
Respondents retained for analysis (cleaned sample)	76

As a robustness check, sensitivity means were computed using the whole raw sample (N=81). As shown in Table 6, retaining the excluded cases increases the overall mean only marginally (3.31 to 3.35) and shifts each dimension by only 0.04–0.05, while preserving the same rank-order profile, indicating that the response-quality exclusions do not drive the reported maturity diagnosis.

Table 6. Sensitivity means (Raw N=81 x Cleaned N=76)

Dimension	Raw mean (N=81)	Cleaned mean (N=76)	Difference (Cleaned-Raw)
ORG	3.329	3.285	-0.044
INF	3.358	3.316	-0.042
DMAN	3.312	3.266	-0.045
ANL	3.391	3.351	-0.040
GOV	3.363	3.321	-0.042
Overall STDAMM	3.352	3.310	-0.043

The HQ–Branch composition was also only slightly affected (raw: 41 HQ/40 Branch; excluded: 1 HQ/4 Branch; cleaned: 40 HQ/36 Branch), as summarized in Table 7. However, because the survey was distributed internally and did not capture completion-time metadata or include attention-check items, other inattentive-response patterns (e.g., speeding, inconsistent responding, or midpoint responding) could not be formally screened, and residual measurement noise may remain. Long-string screening helps reduce extreme satisficing patterns, but it does not eliminate other response biases inherent in internally distributed, agreement-format Likert surveys (e.g., acquiescence/agreeing bias and social desirability pressures in hierarchical settings). Accordingly, Section 4.5 triangulates the maturity profile with interview evidence to derive within-case roadmap implications.

Table 7. Sample Composition by Work Unit (HQ vs Branch)

Stage	HQ n (%)	Branch n (%)	Total
Raw (N=81)	41 (50.6)	40 (49,4)	81
LongString Excluded	1 (20)	4 (80)	5
Cleaned (N=76)	40 (52.6)	36 (47,4)	76

Following data cleaning, reliability testing using Cronbach's alpha indicated strong internal consistency. As shown in Table 8, the overall STDAMM scale suggested excellent reliability (α = 0.958). Furthermore, all five dimensions, Organization, Infrastructure, Data Management, Analytics, and Governance, exceeded the recommended 0.70 threshold for exploratory research, indicating strong internal consistency of the STDAMM item sets in this sample.

Table 8. Reliability of STDAMM scale and dimensions (cleaned N=76)

Scale / Dimension	Number of items	Cronbach's α
Overall STDAMM	**24**	**0.958**
ORG – Organization & culture	6	0.735
INF – Infrastructure & technology	3	0.795
DMAN – Data management	4	0.833
ANL – Analytics use	6	0.887
GOV – Governance	5	0.918

To complement the internal-consistency evidence reported above, additional construct-level diagnostics were computed on the cleaned sample (N=76) to support cautious interpretation of the maturity profile in this organizational setting. Table 9 reports composite reliability (CR) and average variance extracted (AVE) [44] for each STDAMM dimension. CR values are adequate across constructs (0.823–0.938), indicating consistent measurement at the composite level, while AVE supports convergent validity for INF, DMAN, ANL, and GOV (0.647–0.753) but is lower for ORG (0.442), suggesting that this dimension captures less shared variance among its indicators in this sample; accordingly, ORG is interpreted more cautiously and the dimension profile is treated as a descriptive diagnostic pattern rather than evidence of sharply separated capability silos.

Table 9. Convergent validity metrics (CR and AVE) for STDAMM dimensions

Construct	k (items)	CR	AVE
ORG	6	0.823	0.442
INF	3	0.880	0.710
DMAN	4	0.889	0.668
ANL	6	0.916	0.647
GOV	5	0.938	0.753

To assess discriminant validity, Table 10 reports the Heterotrait-Monotrait (HTMT) ratios [45] among the five STDAMM dimensions. The HTMT values are elevated in this sample (0.866 to 1.042), with most pairwise ratios exceeding common screening guidelines (0.85 to 0.90) and one ratio above 1.0, indicating substantial construct overlap. Accordingly, HTMT is interpreted here as evidence that respondents perceive the maturity dimensions as tightly coupled, which is consistent with the compressed dimension means reported earlier; therefore, the dimension profile is treated as a descriptive diagnostic pattern, and any fine-grained contrasts across dimensions are interpreted cautiously.

Table 10. HTMT matrix among STDAMM dimensions

	ORG	INF	DMAN	ANL	GOV
ORG	-	0.936	1.042	0.871	0.866
INF	0.936	-	0.979	0.934	0.880
DMAN	1.042	0.979	-	0.963	0.952
ANL	0.871	0.934	0.963	-	0.921
GOV	0.866	0.880	0.952	0.921	-

Because HQ-Branch comparisons are important, internally distributed, cross-sectional surveys, measurement comparability across HQ and Branch was assessed using the Measurement Invariance of Composite Models (MICOM) procedure [46] as a pragmatic invariance screen. Accordingly, MICOM results are used here to clarify the limits of subgroup comparisons. The procedure is not presented as establishing formal measurement equivalence. SmartPLS provides permutation output for Step 3 (see Table 11), but MICOM is evaluated sequentially; therefore, Step 3 mean and variance equality are interpreted only when Step 2 establishes compositional invariance, and for DMAN, Step 3 is not evaluated because Step 2 is not met.

Table 11. MICOM invariance screening summary (HQ=40, Branch=36)

Construct	Compositional invariance (Step 2)	Mean equality (Step 3)	Variance equality (Step 3)	Interpretation
ORG	Yes (p=0.414)	Yes (p=0.561)	No (p=0.039)	Partial invariance; heterogeneity differs
INF	Yes (p=0.829)	Yes (p=0.501)	Yes (p=0.167)	Full invariance; best-supported
DMAN	No (p=0.027)	*Not evaluated*	*Not evaluated*	Not comparable; stop at Step 2
ANL	Yes (p=0.855)	Yes (p=0.509)	No (p=0.008)	Partial invariance; heterogeneity differs
GOV	Yes (p = 0.235)	Yes (p = 0.852)	No (p = 0.010)	Partial invariance; heterogeneity differs

Note: Step 2 p-values are one-tailed (compositional invariance); Step 3 p-values are two-tailed (mean/variance equality). Step 3 is not evaluated when Step 2 is not established (DMAN).

These diagnostics provide additional measurement evidence for interpreting the STDAMM results in this case context. CR values indicate adequate composite-level reliability, while AVE supports convergent validity for most dimensions but is weaker for ORG, so ORG is interpreted more cautiously. HTMT ratios are elevated, suggesting substantial construct overlap and supporting a coupled-profile interpretation rather than sharply separated capability silos. MICOM indicates partial invariance for ORG, INF, ANL, and GOV, but compositional invariance is not established for DMAN; therefore, HQ–Branch contrasts are reported descriptively, and strong subgroup claims are avoided, especially for DMAN.

4.2. Current Maturity Level (RQ1)

Descriptive results from the cleaned sample (N=76) place the overall STDAMM maturity mean at 3.31 on a 5-point Likert scale. The 95% confidence interval (95% CI) for the mean, estimated via nonparametric bootstrap [47], [48] - ranges from 3.15 to 3.46 (see Table 12), indicating that the central tendency of perceived maturity in this respondent pool lies consistently in the low-to-mid "3" range rather than being driven by a small number of extreme responses. Using the predefined score-band mapping (Section 3.3), this mean is categorized as Level 3 (Established). Here, "Established" reflects routinized visibility and regular use of analytics outputs in recurring decision routines, while data governance standardization remains uneven and is framed as a Level 4 benchmark. For roadmap interpretation, Level 4 (Mature) is retained as an aspirational benchmark to express a gap-to-target view.

Table 12. Overall STDAMM maturity classification

Metric	Value	95% CI	Interpretation (within-case)
Overall maturity mean	3.31	(3.15, 3.46)	Respondent-reported overall maturity level
STDAMM classification	Level 3 (Established)	n/a	Classification applied to the assessed respondent pool
Roadmap benchmark used	Level 4 (Mature)	n/a	Aspirational reference for gap-to-target, not an audit threshold

Note: "n/a" indicates not applicable.

This Level 3 classification is consistent with interview descriptions of routine dashboard monitoring, which remains dependent on intensive cross-functional coordination to resolve conflicting figures across sources. Interpreted together, the table and interviews suggest that "established" visibility can coexist with continued reliance on human coordination to stabilize numbers, which is aligned with the paper's positioning of STDAMM as a within-case diagnostic indicator. For item-level transparency without over-interpreting small differences, Appendix A provides descriptive statistics for all 24 STDAMM items (Table A1), while the next section decomposes the overall classification into a dimension-level profile for prioritization.

4.3. Dimensional Analysis and Triangulation

To support within-case diagnosis, the overall Level 3 result is decomposed into a five-dimensional profile. As noted in Section 4.1, the survey administration constrains formal screening of inattentive-response patterns; accordingly, dimension contrasts are interpreted as descriptive cues for within-case triangulation. Table 13 reports dimension means with 95% CI estimated via nonparametric bootstrap [47], [48]. The means are tightly clustered (3.27 to 3.35), and the intervals overlap considerably, suggesting that any cross-dimension contrasts are small in magnitude. Consistent with this, the Friedman test does not detect within-respondent differences across the five

dimensions (chi-square(4)=2.397, p=0.663), and Kendall's W indicates negligible concordance (W = 0.008). Therefore, the rank-order pattern is used only as a pragmatic steering signal for roadmap prioritization.

Table 13. Descriptive statistics by STDAMM dimension

Dimension	Mean	95% CI	Median	Std
ORG	3.29	(3.15, 3.42)	3.33	0.60
INF	3.32	(3.14, 3.49)	3.33	0.79
DMAN	3.27	(3.08, 3.44)	3.50	0.82
ANL	3.35	(3.17, 3.53)	3.50	0.80
GOV	3.32	(3.14, 3.50)	3.40	0.81

Note: 95% CI = 95% confidence interval for the mean, estimated using nonparametric bootstrap (percentile CI) on the cleaned sample.

Accordingly, the quantitative profile is analyzed using a convergence-oriented within-case triangulation logic that integrates the survey pattern with thematic coding of interview data. Table 14 summarizes this joint display by linking each dimension's quantitative signal to (i) day-to-day reporting and reconciliation routines and (ii) governance-oriented implications for roadmap refinement.

Table 14. Within-case triangulation of STDAMM dimension signals and thematic interview evidence

STDAMM dimension	Mean; Gap	Thematic-coded operational pattern (respondent codes)	Roadmap implication
ORG	3.29; 0.71	Operational numbers are stabilized through cross-function reconciliation and sign-off routines rather than a single "owner" for internal reporting objects (R01).	Define decision rights and accountability for shared metrics (who owns definitions, who approves changes, who arbitrates disputes).
INF	3.32; 0.68	End-to-end visibility requires integration across operational systems (e.g., VMS/TMS) to move from descriptive reporting toward near real-time monitoring (R05); manual handoffs indicate fragmented pipelines (R04).	Standardize high-impact data pipelines from production to executive reporting; reduce manual data handling in the reporting layer.
DMAN	3.27; 0.73	Master data and codes are not fully harmonized (service codes, customer IDs), requiring cleansing/adjustment that blocks automation (R03) and drives recurring reconciliation to an authoritative ledger (R01, R04).	Prioritize master-data harmonization for critical entities and measures; formalize reconciliation rules and "authoritative source" hierarchy for KPI production.
ANL	3.35; 0.65	Dashboards already support periodic analysis and operational monitoring (Tableau for comparative analytics; Kibana for near real-time monitoring), indicating established consumption of analytics outputs (R02).	Protect existing dashboard value while shifting effort upstream (data readiness, stability) so analytics outputs become decision-ready with fewer rechecks.
GOV	3.32; 0.68	Governance artefacts and shared definitions are unevenly institutionalized (no clear internal "critical data" list; dictionary discipline not embedded), pushing staff to rely on ad hoc discovery and informal alignment (R01).	Operationalize a corporate data dictionary and stewardship routines (definition ownership, socialization cadence, compliance checks tied to reporting cycles).

Overall, Table 14 shows why a tightly clustered quantitative profile can still be diagnostically meaningful in a within-case sense. The profile indicates established visibility and reporting routines, while the thematic evidence highlights that comparability and trust across units remain dependent on informal alignment practices and incomplete standardization.

4.4. Gap Analysis and Priority Bands (RQ2)

RQ2 concerns how the observed maturity profile can be translated into actionable roadmap implications. This section applies a gap-to-benchmark view by contrasting each dimension's current mean with the Level 4 benchmark specified in the company roadmap. Here, Level 4 serves as an aspirational reference point for within-case planning. Table 15 reports the resulting gap values, computed as Level 4 minus the current dimension mean. Because the gaps fall within a narrow range, the results are summarized as priority bands that support roadmap steering at a coarse level.

Table 15. Gap-to-benchmark analysis and steering bands by STDAMM dimension

STDAMM Dimension	Current Score	Target (Level 4)	Gap	Priority Bands
Data Management (DMAN)	3.27	4.00	0.73	High steering band
Organization (ORG)	3.29	4.00	0.71	High steering band
Infrastructure (INF)	3.32	4.00	0.68	Medium steering band
Governance (GOV)	3.32	4.00	0.68	Medium steering band
Analytics Use (ANL)	3.35	4.00	0.65	Lower steering band

Within this view, DMAN and ORG exhibit the largest benchmark gaps and are placed in the high-priority band. INF and GOV fall into a medium priority band given their similar gap magnitudes, while ANL forms a lower priority band. This banded interpretation is consistent with earlier evidence of a coupled profile, including closely grouped dimension means, overlapping confidence intervals, and construct overlap signals from HTMT. The practical implication is that strengthening foundational enablers in DMAN and ORG can improve the reliability and scalability of analytics outcomes across units and can reduce the operational friction documented in the qualitative evidence.

MICOM screening adds an interpretive qualifier for DMAN. Compositional invariance is not established for DMAN, so the DMAN band should be validated through workstream-level diagnosis across HQ and Branch before being operationalized as a uniform cross-group statement. Table 15, therefore, functions as a planning input that guides sequencing and governance focus areas, to be refined through context-specific validation and implementation design.

4.5. Discussion

The results support a cautious within-case diagnostic reading of PT ABC's analytics maturity and its enabling conditions. Robustness checks indicate that the overall Level 3 classification is not driven by a small number of extreme response patterns. Sensitivity comparisons show only marginal shifts between the raw and cleaned means, and the bootstrap 95% confidence intervals for the overall score and each dimension suggest a stable central tendency in this respondent pool. At the same time, the dimensional profile is compressed: confidence intervals overlap substantially, the Friedman test does not detect within-respondent differences, and Kendall's W indicates a negligible effect size. Overall, the profile behaves as a coupled system rather than as independent capability domains.

Taken together, the STDAMM profile and the interview evidence point to a governance–capability misalignment that is salient for within-case roadmap steering. The empirical interpretation reported here is derived from triangulating survey patterns with operational accounts from interviews. In this case, descriptive analytics appear established, while the definition discipline still depends on recurring reconciliation to resolve inconsistent figures across systems and on limited socialization of shared dictionary practices. This interpretation is also consistent with the Indonesian case literature ("Dinas Parpora" and "PT XYZ") [32], [39], where technology investments often precede the institutionalization of governance routines. The practical implication is to strengthen the foundations that make analytics outputs more comparable, repeatable, and decision-ready across units, while sustaining the gains in analytics visibility.

Based on the gap to benchmark view in Table 15, the 2025 to 2026 roadmap can be refined by emphasizing foundation building in three areas:

1) Standardization: operationalize a corporate data dictionary and shared definitions for critical reporting objects to reduce reconciliation rework and definition drift.
2) Ownership: formalize data steward accountability and escalation routines that connect business report owners with technical custodians.
3) Master Data Harmonization: agree and document authoritative sources for high-impact entities (for example, customer and product) to stabilize upstream consistency required for scaling analytics beyond descriptive reporting.

Interpretation remains bounded by the survey-administration constraints (Section 4.1) and the MICOM screening results (Table 11); subgroup contrasts should therefore be treated cautiously.

5. CONCLUSION

Based on a qualitative-first, sequential mixed-method diagnostic case design (Section 3.1), this study provides a within-case diagnosis of PT ABC's perceived analytics capability maturity using STDAMM. The respondent pool's aggregate maturity is classified as Level 3 (Established). Consistent with the purposive, management-led respondent pool, the findings are presented as internal steering signals rather than organization-wide estimates.

Substantively, the maturity profile suggests that descriptive reporting routines and tool-supported analytics use can appear relatively established while the enabling foundations for scale and comparability remain uneven. In the gap-to-benchmark view used in this study, the largest diagnosed gaps sit in Data Management and Organization, which aligns with the paper's triangulated interview accounts describing recurring definition inconsistency and the prevalence of procedural workarounds that stem from uneven ownership mechanisms. Practically, the roadmap implications emphasize Standardization, Ownership, and Master Data Harmonization (Section 4.5). These actions are framed as implementation priorities to improve cross-unit comparability and decision readiness of analytics outputs, providing a baseline for future capability development.

Theoretically, the case adds evidence that analytics maturity can manifest as a coupled system in which progress in infrastructure and analytics use does not automatically translate into comparable, trusted, and scalable decision support when data management and organizational enablers lag. The study also illustrates a cautious measurement approach for maturity profiling in complex, internally distributed survey settings by combining response-pattern screening with construct-level diagnostics and a pragmatic group-comparability screen. Boundary conditions remain important (Sections 3.1 and 4.1): the survey is cross-sectional, self-reported, and internally distributed, and subgroup comparisons should be treated cautiously where measurement comparability is not equally supported across constructs. Future research can extend this work through longitudinal measurement around roadmap initiatives, broader branch-balanced sampling, and multi-case comparisons across logistics and financial state-owned enterprises, complemented by objective operational indicators to triangulate perception-based maturity scores.

ACKNOWLEDGEMENTS

The corresponding author gratefully acknowledges the Indonesia Endowment Fund for Education (Lembaga Pengelola Dana Pendidikan/LPDP), Ministry of Finance of the Republic of Indonesia, for funding his master's studies under the Domestic Magister Scholarship Program.

REFERENCES

[1] B. Marr, *Data Strategy: How to Profit from a World of Big Data, Analytics and the Internet of Things*. London, U.K.: Kogan Page, 2017.

[2] S. Klee, A. Janson, and J. M. Leimeister, "How data analytics competencies can foster business value, A systematic review and way forward," *Information Systems Management*, vol. 38, no. 3, pp. 200–217, 2021, doi: 10.1080/10580530.2021.1894515.

[3] Danantara Indonesia, "About Danantara," 2025. [Online]. Available: https://danantara.id/about-us/. [Accessed: Dec. 03, 2025].

[4] Kompas.com, "Danantara kenalkan tagline baru 'Melayani dengan sepenuh hati'," Oct. 31, 2025. [Online]. Available: https://money.kompas.com/read/2025/10/31/134600526/danantara-kenalkan-tagline-baru-melayani-dengan-sepenuh-hati--. [Accessed: Dec. 03, 2025].

[5] OECD, *Competitive Neutrality Reviews: Small-Package Delivery Services in Indonesia*. Paris, France: OECD Publishing, 2021, doi: 10.1787/24542e61-en.

[6] PT ABC, "Rencana transformasi tata kelola data dan informasi PT ABC 2025–2026," internal document, unpublished, 2025.

[7] PT ABC, "Hasil Asesmen Tata Kelola dengan COBIT 2019", internal document, unpublished, 2025.

[8] ISACA, *COBIT 2019 Framework: Governance and Management Objectives*. Schaumburg, IL, USA: ISACA, 2018, ISBN: 978-1-60420-764-4.

[9] M. Spruit and K. Pietzka, "MD3M: The master data management maturity model," *Computers in Human Behavior*, vol. 51, pp. 1068–1076, 2015, doi: 10.1016/j.chb.2014.09.030.
[10] H. Haneem, B. Ali, A. Kama, and N. M. H. Basri, "Determinants of master data management adoption by organizations: An empirical investigation," *International Journal of Information Management*, vol. 45, pp. 25–43, 2019, doi: 10.1016/j.ijinfomgt.2018.10.007.
[11] F. S. Dhitama, I. Eitiveni, and N. P. Utami, "Master Data Management Maturity Model (MD3M) assessment: Case study of PT Graha Segara," *Journal of Social Research*, vol. 4, no. 3, pp. 570–575, 2025, doi: 10.55324/josr.v4i3.2451.
[12] M. Ayomi, A. B. Hidayanto, and N. F. Ayub, "Pengukuran tingkat kematangan big data: Studi kasus PT. XYZ," M.S. thesis, Universitas Indonesia, Depok, Indonesia, 2019.
[13] D. Ioakeimidou, D. Chatzoudes, and P. Chatzoglou, "Assessing data analytics maturity: proposing a new measurement scale," *Journal of Business Analytics*, vol. 8, no. 1, pp. 55–69, Jan. 2025, doi: 10.1080/2573234X.2024.2439990.
[14] S. Soares, *The Chief Data Officer Handbook for Data Governance*, 1st ed. MC Press Online, LLC, 2014.
[15] DAMA International, *DAMA-DMBOK: Data Management Body of Knowledge*, 2nd ed. Basking Ridge, NJ, USA: Technics Publications, 2017.
[16] B. van Gils, *Data Management: A Gentle Introduction*. Zaltbommel, The Netherlands: Van Haren Publishing, 2020.
[17] D. Plotkin, *Data Stewardship: An Actionable Guide to Effective Data Management and Data Governance*, 2nd ed. Cambridge, MA, USA: Academic Press (Elsevier), 2021.
[18] A. Mahanti, *Data Governance and Data Management: Contextualizing Data Governance Drivers, Technology, and Tools*. Singapore: Springer Nature Singapore, 2021.
[19] I. Caballero and M. Piattini, Eds., *Data Governance: From the Fundamentals to Real Cases*. Cham, Switzerland: Springer, 2023, doi: 10.1007/978-3-031-43773-1.
[20] M. Sargiotis, *Data Governance: A Guide*. Cham, Switzerland: Springer Nature Switzerland AG, 2024, doi: 10.1007/978-3-031-67268-2.
[21] M. Fleckenstein and L. Fellows, *Modern Data Strategy*. Cham, Switzerland: Springer International Publishing, 2018, doi: 10.1007/978-3-319-68993-7.
[22] A. Corallo, M. Lazoi, G. Lezzi, and E. Lettera, "Analytics maturity models: A systematic literature review," *Technological Forecasting and Social Change*, vol. 196, art. 122826, 2023, doi: 10.1016/j.techfore.2023.122826.
[23] F. Halper and D. Stodder, *TDWI Analytics Maturity Model Guide: Interpreting Your Assessment Score and Moving Forward*. Renton, WA, USA: TDWI Research, 2014.
[24] S. A. Wulandari, Y. Ruldeviyani, V. Suwiyanto, W. Nurfiantara, M. A. Pasirulloh, and M. Y. Dias, "Data Governance Maturity Level at the National Archives of the Republic of Indonesia," *Jurnal Penelitian Pos dan Informatika*, vol. 10, no. 1, pp. 27–40, Oct. 2020, doi: 10.17933/jppi.v10i1.306.
[25] A. Fahmi, F. M. Wibowo, and N. S. Imaniyati, "Assessing maturity level of big data analytics implementation using TDWI," *IOP Conference Series: Earth and Environmental Science*, vol. 969, no. 1, art. 012055, 2022, doi: 10.1088/1755-1315/969/1/012055.
[26] J. W. Creswell, *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 4th ed. Thousand Oaks, CA, USA: SAGE Publications, 2014.
[27] T. H. Davenport, *DELTA Plus Model and Five Stages of Analytics Maturity: A Primer*. Portland, OR, USA: International Institute for Analytics, 2018.
[28] R. L. Grossman, "A framework for evaluating the analytic maturity of an organization," *International Journal of Information Management*, vol. 38, no. 1, pp. 45–51, 2018, doi: 10.1016/j.ijinfomgt.2017.08.005.
[29] M. O. Gökalp, E. Gökalp, K. Kayabay, A. Koçyiğit, and P. E. Eren, "The development of the data science capability maturity model: A survey-based research," *Online Information Review*, vol. 46, no. 3, pp. 547–567, 2021, doi: 10.1108/OIR-10-2020-0469.

[30] M. O. Gökalp, E. Gökalp, S. Gökalp, and A. Koçyiğit, "The development of a data analytics maturity assessment framework: DAMAF," *Journal of Software: Evolution and Process*, vol. 35, no. 8, p. e2415, 2021, doi: 10.1002/smr.2415.

[31] T. Korsten, T. Reus, M. Meewis, and M. van Engelen, "A capability maturity model for developing and improving advanced data analytics capabilities," *Pacific Asia Journal of the Association for Information Systems*, vol. 16, no. 4, pp. 1–40, 2024.

[32] R. A. Vetian, A. Lelitasari, R. Ilyasa, and R. G. Satria, "Maturity level of data management at the Department of Tourism, Youth, and Sports," *Eduvest, Journal of Universal Studies*, vol. 5, no. 9, 2025, doi: 10.59188/eduvest.v5i9.51469.

[33] J. R. Sihotang, A. N. Hidayanto, and Y. K. Isal, "Assessing BI maturity: Government financial sector case study," *Jurnal Informatika Ekonomi Bisnis*, vol. 7, no. 3, pp. 496–500, 2025, doi: 10.37034/infeb.v7i3.1203.

[34] Ibrahim, P. Hakiki, and S. Mukaromah, "Pengukuran tingkat kematangan sistem informasi akademik STIE XYZ menggunakan framework COBIT 5 domain MEA01," *Jurnal Information System & Artificial Intelligence (JISAI)*, vol. 4, no. 2, pp. 165–172, 2024, doi: 10.26486/jisai.v4i2.103.

[35] D. F. Rachmat, D. Mulyadi, S. Abdullah, S. D. Putrianti, and R. Nurliawati, "Analysis of the governance of One Data Indonesia (SDI) at the Communication and Information Office of Sukabumi City," in *Proc. International Conference on Administrative Science (ICAS 2022)*, 2023, pp. 58–67, doi: 10.2991/978-2-38476-104-3_6.

[36] R. Y. Priastomo, Y. Ruldeviyani, A. Gunawan, and A. N. Utami, "Data governance improvement strategy for peer-to-peer lending sharia in Indonesia: Case study PT ABC," *The Indonesian Journal of Computer Science (IJCS)*, vol. 13, no. 6, Dec. 2024, doi: 10.33022/ijcs.v13i6.4233.

[37] G. Prastuti and Lasmin, "Assessing Analytics Maturity Level in the Indonesian Tax Administration: The Case of Compliance Risk Management," *Scientax: Jurnal Kajian Ilmiah Perpajakan Indonesia*, vol. 2, no. 2, pp. 199–217, 2021, doi: 10.52869/st.v2i2.157.

[38] C. Ko, A. D. Adywiratama, and A. N. Hidayanto, "Master Data Management Maturity Model (MD3M) Assessment: A Case Study in Secretariat of Presidential Advisory Council," in *Proc. 2021 9th International Conference on Information and Communication Technology (ICoICT)*, Aug. 2021, pp. 359–363, doi: 10.1109/ICoICT52021.2021.9527507.

[39] F. Retrialisca and U. Chotijah, "The Maturity Measurement of Big Data Adoption in Manufacturing Companies Using the TDWI Maturity Model," *Journal of Information Systems Engineering and Business Intelligence*, vol. 6, no. 1, pp. 70–78, Apr. 2020, doi: 10.20473/jisebi.6.1.70-78.

[40] D. Krismawati, Y. Ruldeviyani, and R. Rusli, "Master data management maturity model: A case study at statistics business register in Statistics Indonesia," in *Proc. 2019 International Conference on Information and Communications Technology (ICOIACT)*, Yogyakarta, Indonesia, Jul. 2019, pp. 931–936, doi: 10.1109/ICOIACT46704.2019.8938482.

[41] N. Qodarsih, S. B. Yudhoatmojo, and A. N. Hidayanto, "Master Data Management Maturity Assessment: A Case Study in the Supreme Court of the Republic of Indonesia," in *Proc. 2018 6th International Conference on Cyber and IT Service Management (CITSM)*, Parapat, Indonesia, Aug. 2018, pp. 1–7, doi: 10.1109/CITSM.2018.8674373.

[42] A. Kurniawan, "Strategi data quality management pada customer profile untuk mendukung broadband business growth di PT. Telkomsel," M.S. thesis, Universitas Indonesia, Depok, Indonesia, 2017.

[43] A. W. Meade and S. B. Craig, "Identifying careless responses in survey data," *Psychological Methods*, vol. 17, no. 3, pp. 437–455, 2012, doi: 10.1037/a0028085.

[44] J. F. Hair, Jr., G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed. Thousand Oaks, CA, USA: SAGE Publications, 2021.

[45] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science*, vol. 43, no. 1, pp. 115–135, 2015, doi: 10.1007/s11747-014-0403-8

[46] J. Henseler, C. M. Ringle, and M. Sarstedt, "Testing measurement invariance of composites using partial least squares," *International Marketing Review*, vol. 33, no. 3, pp. 405–431, 2016, doi: 10.1108/IMR-09-2014-0304.

[47] B. Efron, "Bootstrap methods: Another look at the jackknife," *The Annals of Statistics*, vol. 7, no. 1, pp. 1–26, 1979, doi: 10.1214/aos/1176344552.

[48] B. Efron and R. J. Tibshirani, *An Introduction to the Bootstrap*. New York, NY, USA: Chapman & Hall, 1993.

APPENDIX A. ITEM-LEVEL DESCRIPTIVE

Table A1. STDAMM item-level descriptive statistics (cleaned N=76)

Dimension	Item	Item focus	Mean	SD
Organization	ORG1	Sponsorship and partnership between business and IT for analytics	3.239	0.920
Organization	ORG2	Shared analytics roadmap and disciplined change execution	3.348	0.834
Organization	ORG3	Active steps taken toward using big data analytics	3.328	0.875
Organization	ORG4	Well-defined and repeatable process for analytics funding	3.224	0.915
Organization	ORG5	Funding led by business (not only IT) and not ad hoc bootstrapping	3.322	0.888
Organization	ORG6	Data is used to drive business and operational decisions	3.348	0.834
Infrastructure	INF1	Repeatable processes and tools for developing big data analytics	3.118	0.909
Infrastructure	INF2	The right technical skills for new big data infrastructure technologies	3.132	0.937
Infrastructure	INF3	Ability to adapt quickly by modifying analytics infrastructure	3.276	0.860
Data management	DMAN1	Effective integration of all types of collected data	3.329	0.817
Data management	DMAN2	Ability to analyze all types of collected data	3.303	0.826
Data management	DMAN3	Methods to process big data as it enters the environment	3.276	0.860
Data management	DMAN4	Use of the ERP system to manage operations	3.158	0.915
Analytics	ANL1	Large, established analytics team (e.g., data scientists, modelers)	3.342	0.862
Analytics	ANL2	Users across varying analytic skill levels use big data analytics	3.369	0.824
Analytics	ANL3	Use of diverse data types (structured, unstructured, real-time, internal, external)	3.303	0.826
Analytics	ANL4	Use of advanced analytics methods (predictive, data mining, advanced stats)	3.355	0.819
Analytics	ANL5	Use of big data analytics for cost savings	3.303	0.826
Analytics	ANL6	Use of big data analytics to improve decision-making	3.355	0.819
Governance	GOV1	Documented policies for big data management and analytics	3.342	0.862
Governance	GOV2	Clear data ownership and access policies	3.382	0.849
Governance	GOV3	Policies and methods for data retention	3.368	0.842
Governance	GOV4	Security policies are in place and enforced for all forms of data	3.395	0.837
Governance	GOV5	Security measures to control and monitor data access	3.303	0.826