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DEVELOPING AN ASSET DATA QUALITY INDEX TO STRENGTHEN ACCOUNTABILITY IN HIGHER EDUCATION

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ABSTRACT

Incomplete, inconsistent, outdated, and untraceable fixed-asset records can weaken financial reporting, asset safeguarding, maintenance decisions, and institutional accountability in higher education. This study aims to develop and conduct a design-stage evaluation of an Asset Data Quality Index (ADQI) for measuring the fitness of fixed-asset master data for accountability purposes. Using Design Science Research, seven dimensions, completeness, accuracy, consistency, timeliness, uniqueness, validity, and traceability were translated into field-level rules, record level scores, organizational unit indicators, classification safeguards, and an exception-management workflow. The artifact was designed for a population of 20,789 fixed-asset records at the Public University. At the current stage, evaluation was limited to analytical rule verification and internal-consistency assessment, covering the clarity of dimension definitions, reproducibility of pass/fail rules, consistency of scoring and aggregation procedures, identification of authoritative data sources, and specification of accountability responsibilities. The design-stage findings indicate that the artifact is sufficiently specified for subsequent empirical implementation and that completeness alone is insufficient to represent asset-data quality. Accuracy and traceability require additional documentary and physical evidence. This study does not report empirical ADQI rankings across organizational units because expert review, inter-rater testing, sensitivity analysis, and validation against stocktaking outcomes have not yet been completed. The study contributes an integrated measurement mechanism combining decomposable quality scores, a minimum-dimension safeguard, and an accountable exception-closure process that can initially be implemented in spreadsheets and subsequently integrated into institutional asset information systems.

Keyword: Accountability, Asset Management, Data Governance, Data Quality, Higher Education

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I. INTRODUCTION

Higher-education institutions depend on fixed assets to deliver teaching, laboratory, field, and administrative services. Accountability for those assets depends not only on whether transactions are recorded, but also on whether the underlying data are complete, accurate, consistent, timely, unique, valid, and traceable. When asset registers contain blank custodians, duplicate identifiers, inconsistent locations, expired useful-life information, invalid codes, or records that cannot be linked to source documents, management cannot demonstrate stewardship efficiently. Data quality therefore influences both the reliability of financial information and the operational ability to locate, safeguard, maintain, and derecognize assets.

Data quality is commonly defined as fitness for use rather than as technical correctness alone. Wang and Strong (1996) established that data consumers assess quality across intrinsic, contextual, representational, and accessibility dimensions. Subsequent assessment frameworks emphasize that dimensions must be operationalized as measurable rules tied to a specific decision context (Pipino et al., 2002; Batini et al., 2009; Kahn et al., 2016). More recent work extends this logic to large and continuously changing datasets, where quality controls must operate throughout the data lifecycle rather than through periodic cleaning alone (Cichy & Rass, 2019; Taleb et al., 2021).

The organizational problem addressed in this study arises from the fixed-asset master data of the Public University. The institutional population comprises 20,789 records covering equipment and machinery, transportation equipment, intangible assets, and other fixed assets. The preceding risk-prioritization study used selected accounting and operational fields to schedule physical verification. That work also exposed a distinct problem: a risk score can only be reliable when the underlying data and evidence trail are fit for the decision. The present study therefore shifts the object of evaluation from asset risk to asset-data quality.

Existing studies provide rich general frameworks for information quality, data governance, audit analytics, and asset lifecycle management, but few translate those concepts into a transparent multidimensional index for comparing the quality of fixed-asset data across organizational units in higher education. Research on asset information highlights the importance of data quality for engineering and lifecycle decisions (Lin et al., 2007; Giglio et al., 2018), while information-systems research links information quality with use and organizational benefits (DeLone & McLean, 2003). The unresolved gap is an operational measurement artifact that connects field-level tests, unit-level accountability, evidence ownership, and corrective action.

Existing data-quality frameworks primarily provide general dimension taxonomies, assessment methodologies, or governance principles. Wang and Strong (1996) conceptualize data quality from the perspective of data consumers, Pipino et al. (2002) explains general assessment procedures, Batini et al. (2009) classify data-quality methodologies, and Cichy and Rass (2019) compare broad data-quality frameworks. These contributions establish an essential conceptual foundation, but they do not provide a fixed-asset-specific artifact that simultaneously defines reproducible pass/fail rules, aggregates result across organizational units, prevents critical weaknesses from being concealed by high aggregate scores, and assigns each exception to an owner, evidence requirement, deadline, and closure status. The novelty of the ADQI therefore lies not in proposing new generic dimensions, but in integrating established dimensions into a transparent measurement and accountability mechanism specifically designed for higher-education fixed assets.

Table 1. Comparison of ADQI with Existing Data-Quality Approaches

Approach	Main focus	Typical output	Accountability mechanism	ADQI advancement
Wang and Strong (1996)	Data consumers' perceptions of quality	Conceptual dimensions	Not specifically operationalized	Converts relevant dimensions into fixed-asset rules
Pipino et al. (2002)	Objective and subjective data-quality assessment	General assessment metrics	Limited issue-closure specification	Links measurement results to accountable owners and evidence

Approach	Main focus	Typical output	Accountability mechanism	ADQI advancement
Batini et al. (2009)	Classification of data-quality methodologies	Methodological framework	Context dependent	Provides a replicable fixed-asset implementation
Cichy and Rass (2019)	Comparison of data-quality frameworks	General framework synthesis	No asset-specific workflow	Integrates measurement, safeguards, and exception closure
Proposed ADQI	Fixed-asset information fitness for accountability	Record and unit-level scores, exceptions, and closure status	Explicit owner, evidence, deadline, review, and escalation	Context-specific measurement and governance artifact

Accordingly, the ADQI represents a context-specific design contribution rather than a replacement for established data-quality theory. It operationalizes prior concepts through a new combination of fixed-asset rules, decomposable scoring, non-compensatory classification, and accountable exception management.

This study develops an Asset Data Quality Index (ADQI) based on seven dimensions: completeness, accuracy, consistency, timeliness, uniqueness, validity, and traceability. It asks three questions. First, how can the seven dimensions be translated into auditable rules for heterogeneous asset records? Second, how can record-level scores be aggregated by organizational unit without concealing a critically weak dimension? Third, how can the index be embedded in an accountability workflow that identifies responsible data owners, evidence requirements, and correction priorities? The study contributes a design artifact, operational definitions, scoring equations, classification rules, dashboard specifications, and a field-validation protocol.

II. LITERATURE REVIEW

2.1 Data Quality as Fitness for Accountability

Data quality is multidimensional because the same record may be complete but inaccurate, accurate but outdated, or valid in format but untraceable to evidence. Accuracy concerns correspondence with an authoritative source or observed condition. Completeness concerns the presence of required values. Consistency concerns agreement across fields, systems, periods, and rules. Timeliness concerns whether data are current enough for the intended decision. Uniqueness concerns the absence of unintended duplicates. Validity concerns conformity with permitted formats, ranges, and reference domains. Traceability concerns whether a record can be connected to its source, custodian, modification history, and verification evidence (Wang & Strong, 1996; Pipino et al., 2002; Batini et al., 2009; Kahn et al., 2016).

The seven dimensions were selected through a relevance-screening process based on the information risks encountered throughout the fixed-asset lifecycle. Completeness is required because each asset must contain the minimum information necessary for recognition, safeguarding, and reporting. Accuracy is required to establish correspondence between recorded information, documentary evidence, and physical conditions. Consistency supports reconciliation across accounting, asset-management, and organizational records. Timeliness captures changes in location, custodian, condition, and utilization that can quickly make otherwise valid records obsolete. Uniqueness prevents duplicate representation and potential overstatement. Validity ensures conformity with institutional codes, formats, ranges, and accounting rules. Traceability connects each record and subsequent modification to its documentary source, responsible person, and verification history. Together, these dimensions cover content sufficiency, factual correspondence, cross-record coherence, currency, identity integrity, rule conformity, and evidence reconstruction. Dimensions such as accessibility, ease of interpretation, and system availability remain important for information-system management but were not included in the core ADQI because the present artifact evaluates

the quality and accountability of fixed-asset records rather than the general performance of the information system.

Asset data make the distinction especially important. An asset may have a nonblank room field and therefore satisfy completeness, yet the recorded room may differ from physical reality and therefore fail accuracy. Two systems may store individually valid asset categories but use incompatible codes, creating inconsistency. A serial number may follow the required format but duplicate another record, violating uniqueness. These examples show why a single missing-value ratio is insufficient. Lin et al. (2007) argue that asset-management data quality should be evaluated in relation to engineering and organizational decisions, while Cichy and Rass (2019) and Taleb et al. (2021) emphasize systematic, continuous quality management.

Information-quality benefits depend on the surrounding information system and organizational process. The DeLone and McLean (2003) model positions information quality as an antecedent of use, satisfaction, and net benefits. Analytics studies similarly show that data generate value only when combined with processes, capabilities, and decision routines (Wamba et al., 2017; Grover et al., 2018; Mikalef et al., 2019). Accordingly, the ADQI is not designed as a decorative dashboard metric. Each score must trigger an accountable correction queue and leave an evidence trail.

2.2 Data Governance and Public Accountability

Data governance specifies decision rights, responsibilities, standards, and controls for data assets. Khatri and Brown (2010) frame governance around principles, quality, metadata, access, and lifecycle decisions. Alhassan et al. (2016) and Abraham et al. (2019) show that governance research repeatedly identifies ownership, stewardship, standards, monitoring, and issue resolution as core activities. These mechanisms are directly relevant to asset registers because the accounting unit, asset custodian, information-technology function, internal auditor, and organizational leadership hold different but interdependent responsibilities.

Accountability requires more than reporting a score. It requires answerability for data conditions, transparency of definitions, traceability of changes, and enforceable follow-up. Risk-based internal-audit research demonstrates the importance of aligning assurance resources with material organizational exposure (Castanheira et al., 2010; Arena & Azzone, 2009; Lenz & Hahn, 2015). Internal auditors may support risk and control processes while preserving their assurance role (Sarens & De Beelde, 2006). In the ADQI architecture, managers own corrections, custodians confirm physical facts, system administrators preserve controlled master data, and internal auditors evaluate rule design, exceptions, and closure evidence.

Audit-analytics research also cautions that larger datasets do not automatically improve judgment. Analytics can expand population coverage, but poor-quality inputs and opaque transformations can create automation bias or false assurance (Earley, 2015; Vasarhelyi et al., 2015; Brown-Liburd et al., 2015; Kokina & Davenport, 2017). A transparent index with decomposable scores, documented rules, and retained exceptions is therefore preferable to a black-box quality prediction during the initial implementation.

2.3 Design Science and Composite Measurement

Design Science Research is appropriate because the research objective is to create and evaluate a purposeful artifact. DSR requires a relevant organizational problem, a rigorously grounded design, an explicit artifact, and evaluation against defined utility criteria (March & Smith, 1995; Hevner et al., 2004). Peffers et al. (2007) structure the process into problem identification, solution objectives, design and development, demonstration, evaluation, and communication. Gregor and Hevner (2013) clarify how design contributions should be positioned, while Venable et al. (2016) align evaluation strategies with artifact maturity and use risk. Geerts (2011) confirms the relevance of DSR for accounting information systems.

Composite indicators provide a concise representation of several dimensions but introduce choices about normalization, weighting, aggregation, and classification. OECD and European Union (2008) recommend making these choices explicit and testing their sensitivity. Equal weighting is used as the baseline in this study because no validated stakeholder preference is yet available. It avoids presenting an untested hierarchy as an empirical fact. A later AHP process can elicit policy weights, provided consistency ratios and sensitivity analyses are reported (Saaty, 1987; Saaty, 2008; Ho, 2008).

The theoretical propositions guiding the design are: P1, asset accountability requires multidimensional data-quality measurement rather than completeness alone; P2, an aggregate index must remain decomposable and include a non-compensatory safeguard so strength in one dimension cannot fully conceal a critical weakness in another; and P3, data-quality measurement strengthens accountability only when scores are linked to ownership, evidence, correction deadlines, and review.

III. RESEARCH METHOD

3.1 Research Design and Context

The study follows a DSR approach and treats the ADQI as an information-system and accounting-control artifact. The organizational context is the Public University. The intended population is the same 20,789-record consolidated asset master used in the preceding fixed-asset risk study. The records cover four asset classes: equipment and machinery, transportation equipment, intangible assets, and other fixed assets. The unit of scoring is the asset record; the unit of managerial comparison is the responsible organizational unit. The case protocol documents context, data sources, rules, evidence boundaries, and evaluation decisions in line with transparent case-study reporting (Runeson & Höst, 2009).

DSR was selected because the primary objective of this study is not only to describe an existing data-quality problem but also to develop and evaluate a purposeful artifact consisting of measurement rules, scoring procedures, classifications, and an accountability workflow. A case-study approach would be appropriate for investigating the fixed-asset data problem in depth within its organizational context, but it would not by itself provide a structured process for designing and evaluating a new measurement artifact. Action research was not selected because the study does not yet involve repeated cycles of organizational intervention, observation, reflection, and collaborative change with practitioners. Conventional system-development methods generally focus on producing a functional information system, whereas the present study focuses on producing a theoretically grounded and evaluable measurement and governance artifact. DSR therefore provides the most appropriate methodological position because it combines problem relevance, artifact construction, theoretical grounding, demonstration, staged evaluation, and communication (Hevner et al., 2004; Peffers et al., 2007; Gregor & Hevner, 2013).

3.2 Design Science Procedure

The six activities are implemented as follows. Problem identification maps data defects that weaken reconciliation and stocktaking. Solution objectives specify a transparent 0–100 quality measure with drill-down evidence. Design and development translate seven dimensions into rules, scores, aggregation, classifications, and workflows. Demonstration applies the rules to the asset-master structure and generates record- and unit-level outputs once the detailed data are executed. Evaluation is organized into a current design-stage evaluation and a subsequent empirical evaluation. The present design-stage evaluation consists of analytical rule verification and internal-consistency assessment. Expert review, inter-rater testing for manually verified fields, sensitivity analysis, and comparison with physical-stocktaking outcomes are planned as subsequent evaluation activities and have not yet been completed. Communication documents the artifact, its theoretical basis, governance requirements, evaluation boundaries, and limitations. Communication documents the artifact, its governance requirements, and limitations.

The research procedure was conducted through the following stages:

1) Problem identification. The researchers identified fixed-asset data problems that could affect reconciliation, stocktaking, reporting, maintenance, transfer, and derecognition.
2) Source identification and data understanding. The researchers identified the consolidated asset master, field dictionary, reference tables, acquisition documents, handover records, custodian information, physical-verification evidence, and system logs required to define and evaluate each rule.
3) Definition of solution objectives. The artifact was required to generate transparent scores on a 0–100 scale, retain record-level exceptions, support organizational-unit comparison, and link each exception to corrective responsibility.
4) Artifact design and development. The seven dimensions were translated into data requirements, pass/fail rules, evidence sources, non-applicable conditions, scoring equations, classification thresholds, dashboard indicators, and an exception-management workflow.
5) Demonstration. The rules were mapped to the structure of the 20,789-record asset population to determine whether each rule could be automated, semi-automated, or required manual verification.
6) Evaluation. At the present stage, the artifact was evaluated through analytical rule verification and internal-consistency assessment. The evaluation examined whether each dimension had a distinct definition, whether each rule could be expressed through reproducible pass/fail criteria, whether the scoring and aggregation procedures were internally consistent, and whether the necessary data and evidence sources could be identified. Expert review, inter-rater testing, sensitivity analysis, and empirical comparison with documentary and physical evidence are reserved for the subsequent evaluation stage, according to the maturity of the evaluation stage.
7) Revision and communication. Findings from the design-stage evaluation were used to refine the definitions, rule structures, scoring procedures, evidence requirements, responsibilities, and reporting specifications. Further revisions based on expert and empirical evaluation will be undertaken during the subsequent implementation stage.

Knowledge sources were identified before rule construction to ensure that every test had an authoritative basis. Conceptual definitions were derived from the data-quality, governance, composite-indicator, and Design Science Research literature. Institutional knowledge was obtained from the asset-master structure, data dictionary, accounting and asset-management policies, reference tables, and discussions with relevant practitioners. Documentary and physical evidence were designated as authoritative sources for rules that could not be evaluated solely from the master data. This procedure distinguishes literature-derived knowledge, institutional rules, system-generated data, and external verification evidence.

3.3 Design-Stage Artifact Evaluation

The present study conducted a design-stage evaluation focusing on four criteria: definitional clarity, rule reproducibility, internal consistency, and implementation feasibility. Definitional clarity was assessed by examining whether each of the seven dimensions represented a distinct data-quality condition. Rule reproducibility was assessed by specifying the unit of assessment, pass criterion, fail criterion, authoritative data source, and non-applicable condition for each rule. Internal consistency was assessed by reviewing the relationships among rule-level results, dimension scores, aggregate ADQI values, minimum-dimension safeguards, and accountability classifications. Implementation feasibility was assessed by mapping each rule to the master-data fields, reference tables, documents, physical evidence, or system logs required for its execution.

This design-stage evaluation establishes whether the artifact is sufficiently specified for subsequent empirical implementation. It does not constitute expert validation, empirical validation of organizational-unit scores, or evidence that ADQI implementation has already improved accountability. Expert review, inter-rater testing, sensitivity analysis, and validation against documentary and physical evidence remain part of the subsequent ex post evaluation stage.

3.4 Dimension Operationalization

Table 2. Operational Definition and Decision Rules of ADQI Dimensions

Dimension	Operational Test	Pass Criterion	Fail Criterion	Authoritative Source	Not-Applicable Condition
Completeness	Test mandatory fields for each active asset record	All fields required for the relevant asset class contain nonblank and non-placeholder values	One or more mandatory fields are blank or contain unauthorized placeholders	Asset-master extract and approved field dictionary	A field is not required for the relevant asset class according to the approved field dictionary
Accuracy	Compare recorded values with authoritative documentary or physical evidence	Recorded acquisition value, serial number, custodian, location, and condition agree with available authoritative evidence	One or more values conflict with authoritative evidence or cannot be substantiated	Invoice, handover document, physical count, serial-number scan, photograph, or signed confirmation	A field does not exist for the relevant asset type; unavailable evidence is classified as unverified, not N/A
Consistency	Compare logically related fields, systems, and accounting periods	Useful life agrees with asset class, unit-location pairing is permitted, and balances reconcile within the approved tolerance	A logical contradiction, prohibited combination, or unreconciled difference is found	Validation matrix, reference tables, accounting ledger, asset subledger, and reconciliation file	Cross-system comparison is not required because the record is legitimately maintained in only one authorized system
Timeliness	Calculate the interval between the evaluation date and the latest approved update or verification	Location, custodian, and condition were updated within the institutionally approved interval	The approved interval has been exceeded or no valid update date is available	System timestamp, verification date, and stocktaking log	The asset is newly recognized and its first verification deadline has not yet occurred
Uniqueness	Compare active records using asset ID, serial number, and an approved composite fingerprint	No other active record has the same unique identifier or confirmed composite fingerprint	An unresolved duplicate identifier or composite fingerprint exists	Asset master, duplicate report, and resolution log	Serial-number testing does not apply to an asset class that is not assigned a serial number
Validity	Test values against approved formats, domains, ranges, and reference relationships	All tested values comply with approved schema, formats, codes, ranges, and reference tables	One or more values fall outside an approved format, domain, range, or reference relationship	Data dictionary, reference tables, schema constraints, and accounting policy	A particular rule does not apply to the relevant asset class or accounting treatment
Traceability	Test whether recognition, changes, responsibility, and verification can be reconstructed	The source-document ID, custodian, updater, timestamp, and required verification evidence are available and linked	One or more required evidence links or change records are missing, invalid, or inaccessible	Document repository, audit log, custodian confirmation, and stocktaking evidence	Change-history testing is N/A when no post-recognition change occurred; source-document traceability remains applicable

Note: A not-applicable classification must be supported by a documented rule and reason. Missing information, unavailable evidence, or an unperformed procedure must not be coded as not applicable. Such conditions are classified as failed or unverified, depending on the nature of the rule.

Source: Authors' design and analysis (2026).

3.5 Scoring and Aggregation

For each asset record i and dimension d, the score is the proportion of applicable quality rules passed. A rule is coded 1 when passed, 0 when failed, and not applicable only when the exclusion is documented. Unknown values are not treated as passed.

$DQ_id = 100 \times (\Sigma$ passed applicable rules / Σ applicable rules)

The record-level ADQI uses equal baseline weights for the seven dimensions. Each weight is 1/7, or 14.29 percent. This choice is transparent and avoids unsupported preference claims.

$ADQI_i = (C_{ompi} + A\square\square_i + C_{onsi} + T_{imei} + U_{ni}q_i + V_{ali} + T_{ra}\square_{ei}) / 7$

The organizational-unit score is the arithmetic mean of record-level ADQI values in the unit. The arithmetic mean is used because each asset record constitutes the same basic unit of assessment and produces a standardized score on the same 0–100 scale. This aggregation method is transparent, easily reproducible, and suitable for comparing the overall condition of asset records across organizational units. However, the arithmetic mean may allow high-scoring records to offset low-scoring records. For this reason, the mean is not interpreted independently. It is accompanied by dimension-level means, failed-rule counts, affected book value, unresolved critical exceptions, and a minimum-dimension safeguard. These additional indicators preserve the visibility of concentrated or material data-quality problems that could otherwise be concealed by the average. Unit-level means may also be influenced by differences in the number, type, value, and complexity of assets managed by each unit. Accordingly, comparisons should be supplemented by stratification by asset class and affected book value during the subsequent empirical implementation.

The dashboard also reports the seven dimension means, failed-rule counts, affected book value, unresolved critical exceptions, and age of open corrections. To prevent compensability, the classification combines the aggregate score with the unit's minimum dimension score.

Table 3. ADQI Classification and Accountability Response

Class	Aggregate Criterion	Minimum-Dimension Safeguard	Required Response
Excellent	ADQI ≥ 90	Every dimension ≥ 80	Maintain controls and quarterly monitoring
Good	80 ≤ ADQI < 90	Every dimension ≥ 70	Correct isolated exceptions within the normal cycle
Adequate	70 ≤ ADQI < 80	Every dimension ≥ 60	Formal improvement plan and monthly monitoring
Weak	60 ≤ ADQI < 70	No safeguard	Prioritized correction and management escalation
Critical	ADQI < 60 or critical evidence failure	No safeguard	Immediate reconciliation, ownership assignment, and audit review

Source: Authors' design and analysis (2026).

The proposed thresholds are provisional managerial decision bands rather than empirically validated cut-off values. The boundaries of 90, 80, 70, and 60 were selected to provide transparent and interpretable ten-point performance intervals with progressively stronger management responses. They should not be interpreted as universal standards or as evidence that a particular score is inherently acceptable. Institutional adoption requires the thresholds to be reviewed against regulatory requirements, historical defect rates, management risk tolerance, asset materiality, stocktaking discrepancies, and remediation capacity.

During the subsequent empirical stage, threshold sensitivity will be assessed by shifting each boundary by five points and observing changes in unit classifications and escalation decisions. The

thresholds will be retained, adjusted, or differentiated by asset class only after sufficient implementation evidence is available. Until that evaluation is completed, the classifications serve as proposed accountability responses rather than validated predictions of institutional performance

3.6 Evaluation Plan

Artifact evaluation is organized into two stages. The first stage, reported in this study, is an ex ante design evaluation covering definitional clarity, rule reproducibility, internal consistency, source-data identification, and implementation feasibility. Each dimension and rule was reviewed analytically to ensure that its meaning, decision criteria, required evidence, scoring treatment, and responsibility assignment were explicitly specified.

The second stage is an ex post empirical evaluation to be undertaken after the rules have been executed on the complete asset dataset. This stage will include structured expert review, inter-rater agreement testing for manually assessed accuracy and traceability rules, sensitivity analysis of weights and thresholds, comparison with physical-stocktaking discrepancies, and evaluation of the time required to identify, assign, correct, verify, and close exceptions. Because this second stage has not yet been completed, the present article does not report validated organizational-unit rankings, criterion-validity results, inter-rater reliability, or evidence of improved accountability outcomes.

Risk interpretation follows the principle that uncertainty must be assessed relative to organizational objectives and consequences (Aven, 2016). Similarly, enterprise risk information should be connected to management action rather than presented as a stand-alone register (Quon et al., 2012).

IV. RESULTS AND DISCUSSION

4.1 The ADQI Artifact

The principal research result is a design-stage measurement and governance artifact consisting of seven-dimension definitions, field-level decision rules, scoring equations, classification safeguards, exception-management specifications, accountability roles, and proposed dashboard outputs consisting of seven-dimension definitions, field-level tests, scoring equations, classification safeguards, exception queues, accountability roles, and dashboard outputs. Unlike the preceding CRI, which prioritizes which assets should be physically verified first, the ADQI is designed to evaluate whether each unit's asset information is sufficiently reliable for reporting, safeguarding, maintenance, and audit decisions. The two models are complementary but not interchangeable: CRI measures exposure priority, whereas ADQI measures information fitness.

Table 4. Distinction Between the Prior CRI and the Proposed ADQI

Element	Composite Risk Index	Asset Data Quality Index
Primary question	Which assets should be verified first?	How reliable and accountable is the asset data?
Unit of output	Priority score for each asset	Quality score for each asset and organizational unit
Dimensions	Value, economic utility, condition, location risk	Completeness, accuracy, consistency, timeliness, uniqueness, validity, traceability
Managerial action	Sequence field stocktaking	Correct data, assign ownership, and strengthen evidence
Validation	Physical findings by priority group	Rule accuracy, stocktaking discrepancies, correction closure, score stability

Source: Authors' design and analysis (2026).

4.2 Design-Stage Evaluation Results

The design-stage evaluation produced four principal findings. First, the seven dimensions represent distinguishable data-quality conditions. For example, a populated location field may pass completeness but still fail accuracy when it does not correspond to the physical location of the asset. Second, the rules can be specified through observable pass, fail, unverified, and not-applicable conditions. This distinction prevents missing evidence from being incorrectly treated as satisfactory data.

Third, the scoring architecture is internally consistent because applicable rule results are first aggregated into dimension scores before the seven-dimension scores are combined into the overall ADQI. The minimum-dimension safeguard limits the ability of strong performance in one dimension to conceal a critical weakness in another. Fourth, the source-data mapping shows that completeness, uniqueness, and most validity rules can be assessed from structured master-data fields, while consistency and timeliness require reference tables, cross-field comparisons, or update timestamps. Accuracy and traceability require documentary or physical evidence and therefore cannot yet be fully evaluated from the asset master alone.

These findings demonstrate the definitional clarity, rule reproducibility, internal coherence, and empirical evaluability of the proposed artifact. They do not demonstrate expert validity, criterion validity, predictive validity, or actual improvements in institutional accountability. No organizational-unit ADQI ranking is reported at this stage.

4.3 Seven-Dimension Diagnostic Logic

Completeness provides the fastest automated diagnostic but must not dominate interpretation. A 100 percent populated register may still contain inaccurate locations, reused serial numbers, invalid categories, or records unsupported by documents. Accuracy is therefore evidence dependent and should be confirmed against source documents and physical observations. Consistency identifies contradictions across fields and systems. Timeliness converts the age of updates into decision risk. Uniqueness prevents double representation. Validity enforces schema and reference rules. Traceability connects the record to responsibility and evidence. Together, these dimensions operationalize fitness for accountability more fully than a missing-value rate.

The design also distinguishes automated, semi-automated, and manual tests. Completeness, uniqueness, and most validity rules can be automated. Consistency and timeliness usually combine automated rules with approved master-data policies. Accuracy and traceability require evidence integration, including acquisition documents, serial-number scans, custodian confirmation, photographs, and change logs. This distinction prevents the dashboard from overstating certainty when evidence has not yet been collected.

4.4 Accountability Architecture

Table 5. Responsibility Matrix for ADQI Governance

Role	Accountability	Key evidence	Escalation trigger
Organizational leadership	Approve policy, thresholds, owners, and remediation resources	Approved governance policy and review minutes	Critical unit score or overdue material exception
Accounting and asset unit	Maintain definitions, reconcile balances, and manage correction queues	Data dictionary, reconciliation, correction log	Unreconciled value or recurring rule failure
Asset custodian	Confirm existence, condition, location, and use	Signed confirmation, scan, photograph	Missing asset or unapproved relocation

Information technology	Enforce access, reference data, logs, and interface controls	Access matrix, validation configuration, change log	Unauthorized change or failed integration
Internal audit	Evaluate rule design, exceptions, overrides, and closure	Audit trail, sample test, override rationale	Unsupported override or unresolved high-risk defect

Source: Authors' design and analysis (2026).

This allocation converts quality measurement into answerability. A failed rule is attached to an owner, due date, evidence requirement, and closure status. The dashboard should therefore show both the ADQI and the unresolved exception backlog. Dashboard literature recommends concise displays that support monitoring and drill-down rather than presenting disconnected visual indicators (Yigitbasioglu & Velcu, 2012). Data governance literature likewise emphasizes that ownership and issue resolution are necessary complements to standards and metrics (Alhassan et al., 2016; Abraham et al., 2019).

4.5 Exception Identification and Closure Process

The exception-management process begins when an automated, semi-automated, or manual rule generates a failed or unverified result. Each exception receives a unique identifier containing the asset record, failed rule, affected dimension, detection date, severity, and available evidence reference. The accounting and asset unit then reviews the exception to determine whether it represents a genuine data defect, an incorrectly configured rule, an approved non-applicable condition, or an unresolved evidence gap.

A confirmed exception is assigned to the responsible data owner together with the required correction, evidence requirement, due date, and escalation level. The responsible owner corrects the data or submits a documented explanation. The accounting and asset unit subsequently reperforms the rule and verifies the supporting evidence. An exception is classified as closed only when the corrected record passes the applicable rule, the evidence is retained, the verifier and completion date are recorded, and any related accounting or physical discrepancy has been reconciled.

Corrections that do not satisfy the rule or evidence requirement are returned to the responsible owner. Overdue, repeated, unsupported, or materially significant exceptions are escalated to organizational leadership and, where appropriate, internal audit. Closed exceptions remain in the audit trail to support recurrence analysis, management monitoring, and subsequent assurance procedures.

4.6 Theoretical and Practical Contributions

The theoretical contribution of this study consists primarily of a conceptual-integration contribution and a measurement-mechanism contribution. First, the study integrates the fitness-for-use perspective of data quality (Wang & Strong, 1996), objective rule-based assessment (Pipino et al., 2002; Batini et al., 2009), data-governance responsibility (Khatri & Brown, 2010; Abraham et al., 2019), and transparent composite-indicator construction (OECD & European Union, 2008) within the fixed-asset context of higher education. Second, it proposes a measurement mechanism that links field-level rules to decomposable record- and unit-level scores while incorporating a minimum-dimension safeguard to address the compensability problem.

The study does not claim to introduce seven entirely new data-quality dimensions. Its theoretical novelty lies in configuring established dimensions into an accountable fixed-asset measurement architecture. In this architecture, traceability functions not only as a technical data characteristic but also as an accountability mechanism because a record cannot support answerability when its source, responsible custodian, modification history, and verification evidence cannot be reconstructed. The propositions therefore explain that multidimensional measurement contributes to

accountability only when measurement results are linked to ownership, evidence, remediation, verification, and closure.

The practical contribution is an implementable index that can begin in a spreadsheet and later migrate to an asset information system or business-intelligence platform. Once empirically implemented, the seven-dimension scores can support unit-level benchmarking, while record-level failed rules can form an operational correction queue, while record-level failed rules form the operational correction queue. The approach supports lifecycle asset management because reliable information is necessary for acquisition, utilization, maintenance, stocktaking, impairment review, transfer, and derecognition (Giglio et al., 2018). It is intended to strengthen the data foundation for risk-based verification and audit analytics for risk-based verification and audit analytics.

4.7 Practical Implications and Implementation Roadmap

For higher-education management, the ADQI provides a structured starting point for identifying which asset-data problems require immediate attention and which can be addressed through routine data maintenance. Management should not use the aggregate score as the sole performance indicator. Dimension scores, material book values, unresolved exceptions, evidence availability, and correction age should be considered together when determining remediation priorities.

For accounting and asset-management units, implementation should begin with an approved data dictionary and a mapping between each rule and its authoritative source. Automated tests may initially focus on completeness, uniqueness, validity, and selected consistency rules. Accuracy and traceability testing should then be introduced progressively by linking acquisition documents, custodian confirmations, physical-verification evidence, and system logs to the relevant asset records.

For information-technology units, the artifact provides specifications for preventive and detective controls. Mandatory-field controls, permitted-value lists, duplicate detection, timestamp retention, access restrictions, and change logs can reduce the recurrence of data-quality defects. The exception workflow can subsequently be incorporated into an asset information system or business-intelligence platform.

For internal auditors, the ADQI can support risk-based sampling and evaluation of data-governance controls. However, the index should not replace professional judgment or direct verification. Auditors should examine rule configuration, exceptions, overrides, evidence sufficiency, closure decisions, and recurring defects. These implementation steps allow institutions to begin with a controlled spreadsheet model before investing in a fully integrated system.

4.8 Evaluation Scope and Validation Needs

The 20,789-record population establishes the implementation context. This DSR phase evaluates the completeness, internal coherence, transparency, and organizational applicability of the measurement artifact. Unit-level ADQI rankings are reserved for the subsequent ex post evaluation, after all rules have been executed and accuracy and traceability have been tested against documentary and physical evidence. The present results therefore support claims about the artifact's design and evaluability, rather than claims that a particular organizational unit already has high or low data quality.

The next empirical stage should execute the rules on the asset master, stratify findings by unit and asset class, and validate accuracy and traceability against physical and documentary evidence. Sensitivity analysis should compare equal weights with expert-derived weights and report changes in unit rankings. Predictive validity can then be tested by assessing whether lower ADQI values are associated with stocktaking discrepancies, longer correction times, or repeated control exceptions. This staged evaluation follows DSR guidance that artifact utility claims should not exceed the evidence produced by the evaluation setting (Venable et al., 2016).

Accordingly, terms such as "validated," "effective," "improved," and "strengthened accountability" should not be interpreted as empirical outcomes at the present stage. The current evidence supports claims regarding artifact design, internal coherence, operational specification, and evaluability. Claims concerning organizational effectiveness, score validity, or accountability improvement require completion of the subsequent expert and empirical evaluation stages.

V. CONCLUSION

This study develops an Asset Data Quality Index as a design artifact intended to strengthen fixed-asset accountability in higher education. The ADQI translates completeness, accuracy, consistency, timeliness, uniqueness, validity, and traceability into reproducible decision rules, standardized scores, proposed organizational-unit indicators, classification safeguards, and an accountable exception-management process. Its principal contribution is not the introduction of new generic data-quality dimensions, but the integration of established dimensions into a fixed-asset measurement mechanism that connects data-quality conditions with evidence, ownership, remediation, verification, and closure.

The design-stage evaluation supports conclusions concerning the definitional clarity, rule reproducibility, internal consistency, and implementation feasibility of the artifact. It also demonstrates that some rules can be evaluated using structured master data, whereas accuracy and traceability require additional documentary and physical evidence. The study does not yet provide expert validation, inter-rater reliability results, empirically validated thresholds, organizational-unit rankings, or evidence that implementation has improved accountability outcomes.

Higher-education institutions may use the proposed artifact as a starting point for developing asset-data controls, exception queues, management dashboards, and risk-based verification procedures. Implementation should begin with rule configuration and automated testing, followed by documentary and physical validation. Future research should conduct structured expert review, execute the rules on the complete dataset, test inter-rater agreement, assess sensitivity to alternative weights and thresholds, and examine whether ADQI scores are associated with stocktaking discrepancies, remediation volume, and exception-closure time.

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