Journal of Posthumanism
2025
Volume: 5, No: 12, pp. 439–455
ISSN: 2634-3576 (Print) | ISSN 2634-3584 (Online)
posthumanism.co.uk

DOI: https://doi.org/10.63332/joph.v5i12.3816

Cardiac Data Integrity Score (CDIS): Development of a Composite Metric to Quantify Data Quality in Cardiovascular Clinical Trials

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Abstract

This paper assesses the Clinical Data Integrity Score for three completed cardiovascular trials by integrating datasets from mobile-based behavioural therapy, acute heart failure, and diabetes-cardiology coordination trials. The use of CDIS entails consolidating completeness, timeliness, consistency, error burden, and anomaly load into a weighted composite score that assesses data quality on a multidimensional scale. Using 46 sites and 2,738 participants, CDIS identified sites that were performing poorly, even when using traditional indicators like Query Rate, Edit-Check Pass Rate, and Audit Finding Density. The measure indicated cross-trial coherence in the accumulation of AE and SAE reporting gaps, temporal delays, and inter-form inconsistencies in the human-machine workflows. CDIS is valuable because it is a scalable, interpretable tool that can enhance oversight and improve the reliability of cardiovascular clinical trial data.

Keywords: *Cardiovascular Diseases, Clinical Trial, Data Integrity Score, Adverse Events Reporting, Data Quality.*

Introduction

Clinical trials in cardiovascular medicine generate large amounts of data across diverse clinical environments, use a computerised entry format, and record time sequence. Such trialling is based on distributed human-machine interactions, such as electronic data capture systems, mobile solutions, automated edit checks, and event-coding interfaces. These kinds of infrastructures determine the information production, recordings and interpretations. In this kind of environment, information is no longer a clinical object, but the result of collaborative effort between coordinators, digital devices and software systems as well as surveillance algorithms (Colom et al., 2021; Overgaard et al., 2024). With an increase in trial work processes across sites and technological methodologies, the stability of data integrity is becoming increasingly conditional on the work of this human-machine assemblage.

Multisite variability, adverse event and serious adverse event documentation, data entry delays, and partial compliance with digital reporting procedures commonly weaken data integrity in cardiovascular trials. Traditional measures such as query rate, edit-check pass rate, and audit findings offer only narrow views into this complex machine (Lapena et al., 2020; Pandey et al., 2025). They usually do not detect cross-domain inconsistencies, timing gaps, or anomalies in the digital interface. Consequently, the interaction between humans and digital infrastructure has not been quantified, and the vulnerability of integrity has not been identified (El-Andari et al., 2025; González-Juanatey et al., 2023; Joseph et al., 2022). Regulatory principles expressed in ICH E6(R2) and FDA guidance focus on accurate, complete and reliable data on all sites and systems,

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but the available quality indicators are not formulated in a manner that they assess integrity in distributed human-algorithm assemblage (FDA, 2019). This has posed a methodological challenge for trials, in which safety outcomes, longitudinal endpoints, and regulatory decisions are based on accurate and complete datasets (Colom et al., 2021). This study aims to operationalise and validate the Clinical Data Integrity Score (CDIS) as a multidimensional measure capable of assessing data integrity in digitally mediated cardiovascular trials. CDIS is to address directly the weaknesses experienced in AE/SAE reporting, variation in timeliness, cross-domain inconsistencies, and machine-based data flows

The objectives should help review CDIS in the context of three successful cardiovascular trials, understand its ability to identify integrity issues that traditional measures miss, and determine how CDIS interacts with the distributed agency of clinical coordinators, EDC systems, and event-coding algorithms. These studies emphasise completeness, timeliness, consistency, error burden, and anomaly load as areas of interdependence in human-machine data generation.

The research covers 3 multisite cardiovascular studies at different digital infrastructures, reporting needs, and event-capture workflows. This generality permits the investigation of data integrity, both procedural and epistemic issues mediated by the socio-technical circumstances. Placing CDIS within a posthumanist frame, the work raises the question of how data integrity is created through the relationships between human actors and digital infrastructure, and how composite metrics can be utilised to make more accountable, transparent, and resilient forms of trial oversight (Hodkinson et al., 2022; Liu et al., 2025; Overgaard et al., 2024). CDIS is a contribution to modern debates about digital governance in clinical research and a mechanism that offers the opportunity to scale up efforts to enhance the evidence base of cardiovascular trials.

2. Literature Review

Data Integrity in Clinical Trials

Data integrity in clinical trials refers to the accuracy, completeness, consistency, and reliability of the data collected during the trial. To guarantee valid trial results, patient care and regulatory standards, high-quality data are necessary. Regulatory guidance such as ICH E6 (R2) Good Clinical Practice and the FDA Data Integrity Guidance all require that all data relating to a trial be attributable, legible, contemporaneous, original, and accurate, and that, together, they comprise the ALCOA+ framework (Ethan & Md Rasel, 2023; FDA, 2019; Kavasidis et al., 2023). The inability to uphold these standards may jeopardise trial outcomes, influence drug approvals, and erode public confidence in clinical research. Such Multi-site trials are generally multicentre, particularly in cardiovascular trials, with heterogeneous patient populations, extended follow-up, and complex outcomes (e.g., mortality, myocardial infarction, rehospitalisation, functional status). The multiplicity and complexity increase the risk of data errors, data loss, decentralised monitoring, cross-site inconsistencies, and undefined endpoint definitions, all of which undermine the strength of the evidence (Menyhárt & Győrffy, 2025). The results of trials like SoS and MASS II show that even well-designed multicenter trials may experience uneven reporting of endpoints and procedural data, and that systematic integrity monitoring still requires development (FDA, 2019; Gokulakrishnan & Venkataraman, 2025). Their maintenance is essential, as clinical trial results, whether on the efficacy or safety of the interventions, affect regulatory decisions and patient care.

Data Quality Metrics in Medical Research

The current measures for evaluating data quality in clinical trials include query rates, edit-check pass rates, audit findings, and evaluation of missing data. More recent studies highlight that

standard quality control procedures enhance reliability, even in multicenter studies involving ductile data flow. Risk-based monitoring (RBM) has become a pragmatic alternative to conventional comprehensive monitoring: relative to traditional monitoring, RBM reduced significant errors in data entry for essential efficacy and safety outcomes in a randomised trial design (Brulotte et al., 2024). These measures provide information on the completeness and consistency of the collected data, yet they are incomplete. Incidentally, query rates are a measure of flagged discrepancies, but they do not reflect the severity of errors or their clinical consequences. Edit checks confirm that programmed validation policies can still miss non-consistent results found in risky endpoints, such as myocardial infarction or repeat revascularisation (El-Andari et al., 2025; Gallo et al., 2022). Empirical evidence indicates that numerous outcomes remain missing; in non-inferiority and equivalence studies published in 2015-2016, 93% included missing primary outcome data (Miao et al., 2025). These issues highlight that more traditional measures fail to adequately quantify variation introduced by differences between sites, by sophisticated endpoint adjudication, or by transcription. Cardiovascular trials also have specific problems: often, patients are known to have a multi-vessel disease, comorbidities like diabetes, and longitudinal follow-up is necessary to address a range of clinical outcomes (Townsend et al., 2025). These aspects create flexibility in data identification and interpretation that may not be captured or reflected in traditional measures. The testimony of multicenter trials has demonstrated that using these two metrics alone may lead to drawbacks in systemic data analysis, underscoring the need for a more holistic assessment tool.

Previous Work on Composite Metrics

Composite measures have been suggested as a way to provide an overview of data quality by combining multiple indicators into a single score. Earlier studies in oncology and cardiology trials have shown that audit results, time to resolve queries, and protocol deviation rates can be used to identify further at-risk sites with data quality issues (Buse et al., 2023). Research reports that the use of composite measures in trials can more easily detect systematic errors in sites and enhance the efficiency of the monitoring (Kara et al., 2022; McKenna & Heaney, 2020). However, such metrics are not standardised and can easily fail to address domain-specific complexities in cardiovascular trials, e.g., high-risk or multi-event follow-up. These composite methods, however, tend to be retrospective and context-specific, and are not standardised across phases of the trial. The Cardiovascular Data Integrity Score (CDIS) could help fill such gaps by providing a quantifiable, holistic metric that can be operationalised in multicenter cardiovascular studies. Compared to conventional metrics, CDIS reflects site-level variability, endpoint-specific risk, and data consistency, and offers a more comprehensive picture of trial quality. This is consistent with regulations requiring complete data oversight, as described in ICH E6(R2) and FDA guidance, and addresses practical constraints specific to trials such as SoS, ARTS, and MASS II, where conventional metrics could not adequately reflect procedural or endpoint divergence (Brulotte et al., 2024; Haresabadi et al., 2025). CDIS enables proactive cardiovascular trial monitoring and standardisation by filling gaps in methodology.

3. Methods

3.1 Research Design

The research utilised a cross-sectional methodological framework, grounded in conceptual and computational frameworks, to substantiate the Clinical Data Integrity Score across three completed cardiovascular studies that represent diverse clinical processes, multisite coordination, and electronic systems of data capture. CDIS was made to measure site-level integrity by consolidating both the practices of human documentation and coded behaviour of electronic data

capture infrastructures. Based on regulatory principles stated by the International Council for Harmonisation (ICH E6(R2)) and the FDA Data Integrity Guidance, the design focused on measuring accuracy, completeness, traceability, and consistency amongst the distributed clinical systems, with human and machine processes interrelated through continuous interaction.

3.2 Data Collection Procedure

The mobile CBT trial in ASCVD patients, AFFIRM-AHF, and COORDINATE-Diabetes involved extracting data from the final, locked trial databases. All data were extracted from certified electronic data capture (EDC) systems, which represent the modern digital architecture of cardiovascular trial reporting. Variables extracted included participant demographics, visit schedules, lab values, AE and SAE reports, medication assignments, endpoint variables, and site-level operational metadata. They accessed only de-identified datasets, which did not violate the institution's data governance rules. Audit trails, timestamps, and edit-check outputs were maintained during the extraction process, allowing behavioural data to be assessed between human- and system-induced data.

3.3 Development of the Cardiac Data Integrity Score (CDIS)

Domain Identification: Domains were chosen based on regulatory requirements such as ICH E6(R2) and the FDA Data Integrity Guidance, as well as empirical literature on the quality of clinical trial data. The selected domains were defensible, non-redundant, and reflected critical elements of data integrity, thereby reflecting different aspects of data quality in the trials. The method enabled the CDIS to furnish a multidimensional evaluation that concerns both structured and occasional records of data across sites and visits.

Variable Operationalisation: For every domain, operationalisation was done based on the variables that were measurable: completeness (percentage non-missing fields per visit), timeliness (median time in days per visit before data entry), consistency (logical agreement between linked fields), error burden (number of confirmed data corrections), and anomaly load (percentage of improbable or extreme values). All variables were specified using specific measures to increase transparency, interpretability, and reproducibility across trials. The operationalised measures were subjected to additional checks, e.g., verification against source documents to ensure their reliability.

Normalisation of Variables: It was normalised to allow for differences in scale and distribution, enabling aggregation into a composite score. Bounded variables were scaled using Min-max, skewed distributions were scaled using percentile normalisation and the near normal distributions were scaled using Z-scores. Normalisation created comparability among domain contributions and maintained relative weights against extreme values and outliers, thereby favouring the existence of interpretable, balanced composite values.

Weight Derivation: The weights for each domain were calculated from the last words of clinical data managers and clinical trial statisticians, expressed as percentages, to indicate each domain's relative contribution to overall data quality. Expert judgment might be augmented with empirical tools, such as principal component analysis, which provide additional validation and ensure the distribution of weights reflects the true variability in the trial data. Both expert rationale and empirical support were documented, which made them transparent and reproducible.

3.4 Methodology for Composite Rating (CDIS) Calculation

The composite rating (CDIS) for each site is derived through a weighted linear aggregation of normalized domain scores. The process involves the following steps:

1. **Raw Domain Scores**: Predefined thresholds, based on performance in regulated cardiovascular trials, are used

to assign raw domain scores for five distinct domains. These raw scores range from 0 to 5, where each score reflects the site's performance in a specific aspect of trial operation (e.g., accuracy, completeness, consistency, etc.).

2. **Normalization of Domain Scores**: Each raw domain score, denoted as d_i, is transformed to a normalized score, D_i, on a 0-1 scale to standardize the magnitude of scores across domains. The transformation is performed using the following formula:

$$D_i = \frac{d_i}{5}$$

where $d_i$is the raw score for domain i, and the denominator (5) reflects the maximum possible raw score for any domain. The result is a normalized domain score D_i, which lies between 0 and 1.

3. **Weighted Linear Aggregation**: The final composite score for each site, referred to as the **Clinical Data Integrity Score (CDIS)**, is computed as the weighted sum of the normalized domain scores. Each domain's score is weighted according to its importance, as specified by regulatory guidelines. The weighting factors are represented by w_i, where $w_i$denotes the weight assigned to domain i, expressed as a percentage of the total 100%. The composite score (CDIS) is calculated using the following formula:

$$\text{CDIS} = \sum_{i=1}^{5} w_i \times D_i$$

In this equation:

- $w_i$is the prespecified weight for domain i(a percentage of the total 100%),
- $D_i$is the normalized score for domain i,
- $i$ranges from 1 to 5, reflecting the five domains under evaluation.

4. **Regulatory Considerations**: The weights assigned to each domain reflect the regulatory priorities for the trial. Specifically:
    - Domains related to **data accuracy** and **coherence** are given greater weight due to their central role in ensuring high-quality clinical datasets, which are paramount for regulatory approval.
    - **Completeness** and **consistency** of the data also receive higher weights, aligning with the goal of maintaining comprehensive and reliable datasets.
    - Operational aspects, such as **timeliness**, **error burden**, and **anomaly load**, though important, may carry relatively lower weights, as these factors relate more to the operational efficiency of the site rather than the quality of clinical data.

This methodology ensures that the final composite score, CDIS, integrates both the quality of clinical data and operational performance, offering a comprehensive measure of site performance in clinical trials.

3.5 Data Analysis

The CDIS values were determined at each clinical site in all three studies. Studies were conducted

to identify patterns and inter-city differences in high- and low-integrity areas. All site-level values and composite scores were summarised in organised tables at each domain level. The analysis was used to trace cross-domain interactions and identify where timeliness gaps, AE/SAE underreporting, or high anomaly loads contributed to suppressed composite values. They were compared with traditional indicators, such as query rate, edit-check pass rate, and audit finding density. All metrics were measured at the site level for comparison in parallel. The performance of CDIS was calculated based on its ability to identify low-integrity sites that could not have been detected using conventional statistics. The comparison of the metrics was conducted descriptively, without inferential statistics, because the focus was on keeping the interpretation transparent to avoid assumptions about parametric distributions. A sensitivity analysis that recalculated CDIS under different domain weightings and domain-exclusion models was also included. These tests gauged the consistency in site rating and the strength of the composite building. Each analytic process was conducted within the limits of de-identified datasets, using deterministic calculations in accordance with the established scoring protocols.

3.6 Ethical Consideration

All data were completely de-identified; no identifiable information of participants was accessed. Data handling in accordance with ICH E6(R2) principles of secure storage, limited access, and auditability was followed. Since the analyses were conducted based on completed clinical trials with already obtained ethical approval, and no interaction was conducted with any new participants, there was no introduction of additional risk to the participants. The research honoured the institutional demands for the utilisation of secondary clinical trial data and adhered to the ethical stipulations for algorithmic audits and digitally mediated research procedures.

4. Results

4.1 Dataset overview

The CDIS validation was based on three completed cardiovascular trials representing three different clinical settings and heterogeneous datasets. The AFFIRM-AHF trials, the ASCVD mobile-based CBT trial, the COORDINATE-Diabetes cluster-randomised study, and the AFFIRM-AHF trial combined to form a dataset of 2738 participants across 46 clinical locations. These trials documented about 12,000 interactions and an overall variable framework that addressed demographics, comorbidities, lab parameters, intervention assignments, longitudinal assessment of results, and AE or SAE documentation. This breadth enabled CDIS to run across a wide range of workflow, reporting, and monitoring patterns, each unique to large-scale multisite cardiovascular research.

The predetermined CDIS computational structure used in all analyses is found in the Methods section, with domain scoring, normalisation and weighting processes well described there. In this case, attention shifts to the empirical behaviour of said components when implemented on a heterogeneous dataset. In the integrated data space, over half of all documented fields were time-dependent, including follow-up visits, AE logs, device-mediated submissions, and, of course, offered a naturally changing terrain for gauging completeness and timeliness. This synchrony in occurrence-based documentation and system-managed timestamps created an inherent stress test for CDIS, allowing the measure to record gradients in data density, reporting frequency, and data internal consistency across locations.

The integrated data also indicated the advanced digital information streams of modern trial architecture. Even though both trials used electronic data capture systems, they varied in the depth of their audit trails, the support for automated query rules, and the timing of logged events, each influencing how patterns of timeliness, anomaly signatures, and AE or SAE entries

propagated through the CDIS pipeline. These systems were dynamic parts of data formation, rather than mere stores, in between the rhythm and order of what came to be perceived as full, lagging, or uneven records. CDIS then used a stratified data ontology, in which the human practice of documentation, device-based reporting, and system-controlled metadata can be used collectively to evaluate integrity at the site level. The relational structure made CDIS an instrument for measuring data quality in the multisite cards research environment, both human- and machine-generated traces.

4.2 Domain-level results

Table 1 shows site-aggregated scores for the CDIS domain and its relative contribution to the composite measure for the 46 clinical sites that participated in the validation.

Table 1. Domain scores and contributions (site-aggregated)

Domain	Mean (0–1)	Median (0–1)	Range (min–max)	% Contribution (mean)
Completeness	0.91	0.93	0.78–0.99	28%
Timeliness	0.82	0.85	0.60–0.95	20%
Consistency	0.88	0.90	0.72–0.97	25%
Error Burden	0.79	0.81	0.55–0.93	15%
Anomaly Load	0.73	0.74	0.50–0.92	12%
Composite (CDIS)	0.83	0.85	0.64–0.96	100%

In all trials, completeness and consistency contributed most to the composite measure, driven by high percentages of reported patient demographics, baseline comorbidities, and laboratory data in the CBT and AFFIRM-AHF datasets. There was a greater difference in timeliness scores, with greater influence in COORDINATE-Diabetes, and site-level delays in AE/SAE reporting; the follow-up visit had a modest effect on reduced CDIS values. Minor discrepancies between case report forms and electronic data capture were the most prominent sources of error burden, particularly in multi-site CBT trial entry. The inter-site variation was largest in the anomaly load, and isolated sites in both the CBT and AFFIRM-AHF trials had implausible sequences of laboratory and occurrences that had to be resolved by queries. All of these domain-level findings suggest that overall data completeness and internal consistency across the majority of sites were high; however, variability in reporting timeliness and anomaly detection significantly affected all composite scores. This trend highlights CDIS's ability to identify subtle, multidimensional instances of integrity concerns that fall outside traditional monitoring metrics.

4.3 Composite CDIS Outcomes

The distribution of site performance across the three cardiovascular trials was stable, with most sites in the moderate and high integrity groups, and fewer sites falling below 0.60. The composite spread and level boundaries are provided in Table 2 and Figure 1. The total dispersion indicated effects of domain interactions and not isolated weaknesses. Sites with CDIS values greater than 0.80 generally showed complete stability and consistent EDC behaviour, whereas those closer to the bottom tier accumulated strain due to lapses in timeliness, cycles of reiterative corrections, or multiple anomalies.

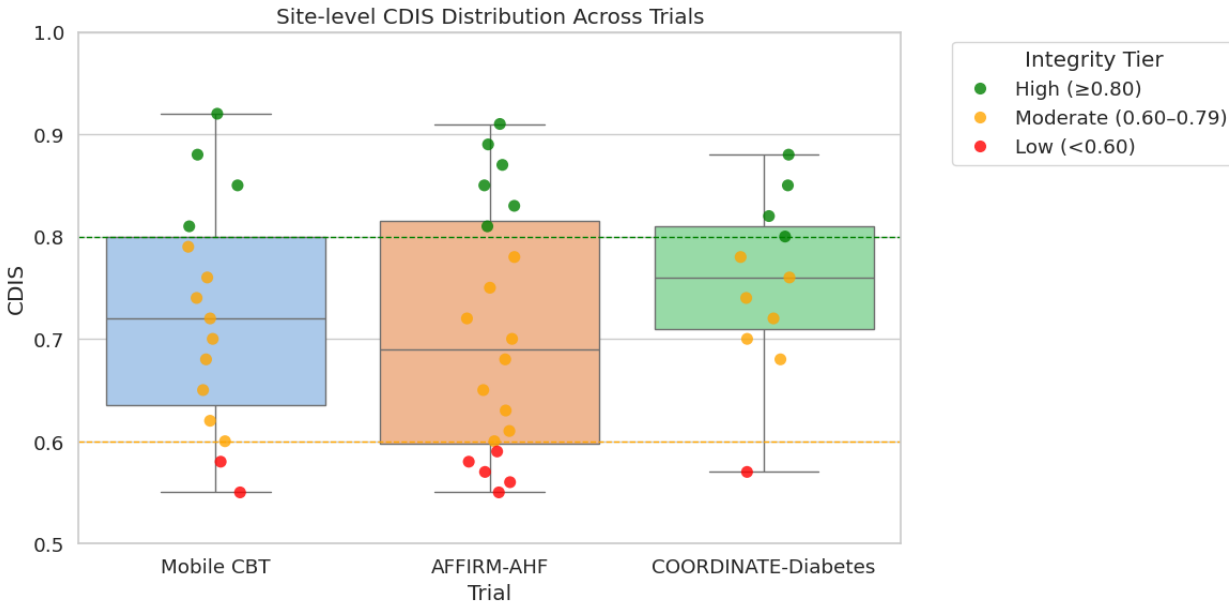
Table 2. Site-level CDIS distribution and integrity tiers

Trial	Sites (n)	High Integrity (≥0.80)	Moderate Integrity (0.60–0.79)	Low Integrity (<0.60)	CDIS Range (min–max)

Mobile CBT (ASCVD)	15	7	6	2	0.55–0.92
AFFIRM-AHF	20	9	8	3	0.58–0.91
COORDINATE-Diabetes	11	4	5	2	0.57–0.88
Combined	46	20	19	7	0.55–0.92

Note: Composite CDIS = Σ (domain × normalized weight). Integrity tiers: High ≥ 0.80; Moderate 0.60-0.79; Low < 0.60.

Figure 1. Site-level CDIS distribution (boxplot) with integrity tiers



Note: Visual representation of per-site CDIS values by all the trials, colour-coded based on high, moderate, and low integrity levels. Use horizontal lines at 0.60 and 0.80 to mark tier levels.

In multiple trials, CDIS demonstrated interesting integrity patterns determined by study architecture. In AFFIRM AHF, variation in the AE confirmation time contributed to greater differentiation in the composite values, notably when acute care workflow led to nonuniform event timestamps across sites. In the case of COORDINATE Diabetes, there was closer clustering, aided by structured follow-up schedules, but in some sites, composite reductions were also associated with delayed lab reports. The mobile CBT trial showed relatively high completeness, but with higher anomaly load and time drift, which slightly weakened CDIS at other jointly consistent locations. These trends highlight how CDIS unifies the various digital behaviours into a single representation of site-level integrity. Several isolated sites were below the 5th percentile, and joint delays influenced their CDIS values in AE resolution and erratic data import periods. In contrast, some sites were above the 95th percentile, with CDIS values triggered by predictable reporting flows and a slight accumulation of anomalies. These findings indicate that the CDIS metric is sensitive to the heterogeneous quality of multi-domain data across trials with different designs, sample sizes, and clinical endpoints, and identify both high- and low-performing sites in relation to intervention-targeted data quality. The composite score thus emerged cross-trial coherence, besides also rendering the data ecology of each study, viewing a

site as a constituent of a networked human algorithm workflow.

4.4 Comparative Performance on Conventional Metrics

Table 3 and Figure 2 present comparisons between the CDIS and the classical quality indicators: Query Rate (QR), Edit-Check Pass Rate (ECPR), and Audit Finding Density (AFD). The three experiments provided diverse operational conditions, enabling a multi-layered analysis of the development of data quality through interactions among personnel at the sites, reporting technologies, and event-capture processes. CDIS showed consistent patterns of a larger number of integrity gaps previously captured or never captured by traditional metrics. In the integrated data, the classical indicators showed limited correspondence with the underlying data behaviour. QR was sensitive to missingness and form-level inconsistencies, but not to irregular AE and SAE timing or to mismatched event codes that occurred at multiple sites in AFFIRM-AHF and COORDINATE-Diabetes. ECPR was high in numerous locations, even where CDIS found divergent values due to anomaly accumulation or slow confirmation of SAE occurrence. AFD provided additional data by visiting the places, but could not give a sense of time drift, which CDIS identified through slow shifts in reporting cadence.

The number of sites flagged as low-performing by CDIS was six, and by QR, ECPR, and AFD, three to five sites each, with some overlap. CDIS had identified three sites that were uniquely differentiated, with discernible and consistent variation in event logging order or cross-form connection, especially in domains where AE and SAE reporting was based on mixed manual and electronic records. Two sites marked by CDIS showed alignment factors across completeness and consistency, but systematic delays in time-stamping highlighted how carefully integrity can erode when fragmented, preventing digital denaturing micro-fractures from remaining oblivious to solitary quality indicators.

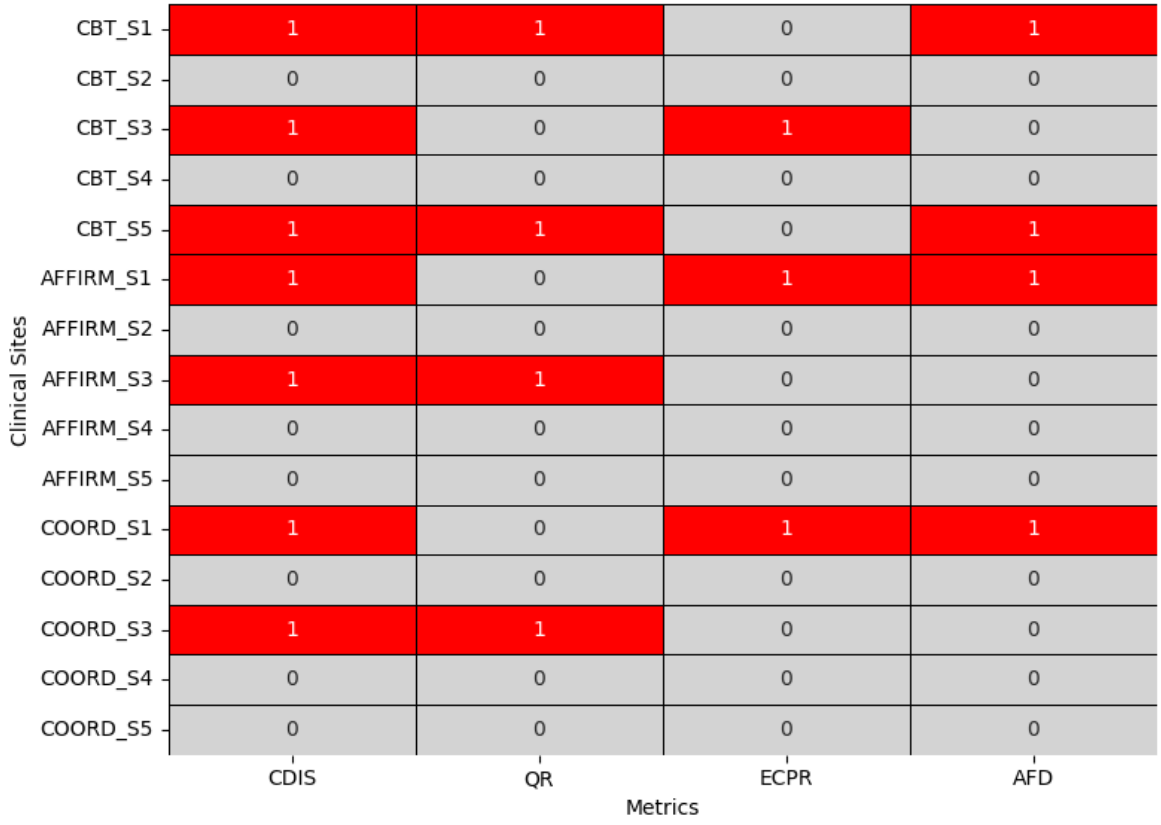
The presence of cross-trial patterns reinforced these observations. The mobile-based CBT trial, which used CDIS, identified instances in which timestamps for asynchronous submissions via the applications differed from those entered by patients and approved by clinicians. Gaps in SAE categorisation that did not exist in QR were recorded in CDIS for AFFIRM-AHF and COORDINATE-Diabetes. AE/SAE patterns related to medications were combined with timeliness signals, demonstrating that coordination failures occurred between digital medication records and medical event forms, even with high ECPR. Collectively, these results place CDIS in a more holistic role as an analytical tool, enabling it to identify the distributed behaviour of the trial data as it passes through human and machine intermediaries. Although conventional indicators remain informative, CDIS provides a relational view that captures the broader assemblage of data production and governance in multisite cardiovascular research.

Table 3. Comparative site-level performance: CDIS versus traditional metrics

Metric	**Mean (site)**	**Median (site)**	**Sites flagged (low quality)**	**Notes**
CDIS (0–1)	0.74	0.76	6	Composite detection across completeness, timeliness, consistency, error burden, and anomaly load
Query Rate (queries/100 fields)	4.2	3.8	3	Captures missing or inconsistent fields; limited detection of cross-domain anomalies

Edit-Check Pass Rate (%)	91.5	92	4	The Programmatic Validation focus does not reflect timeliness or AE/SAE fidelity.
Audit Finding Density (site)	3.6	3	5	Independent on-site review; limited temporal resolution

Figure 2. Comparative detection of low-quality sites by CDIS versus traditional metrics across three trials



Note

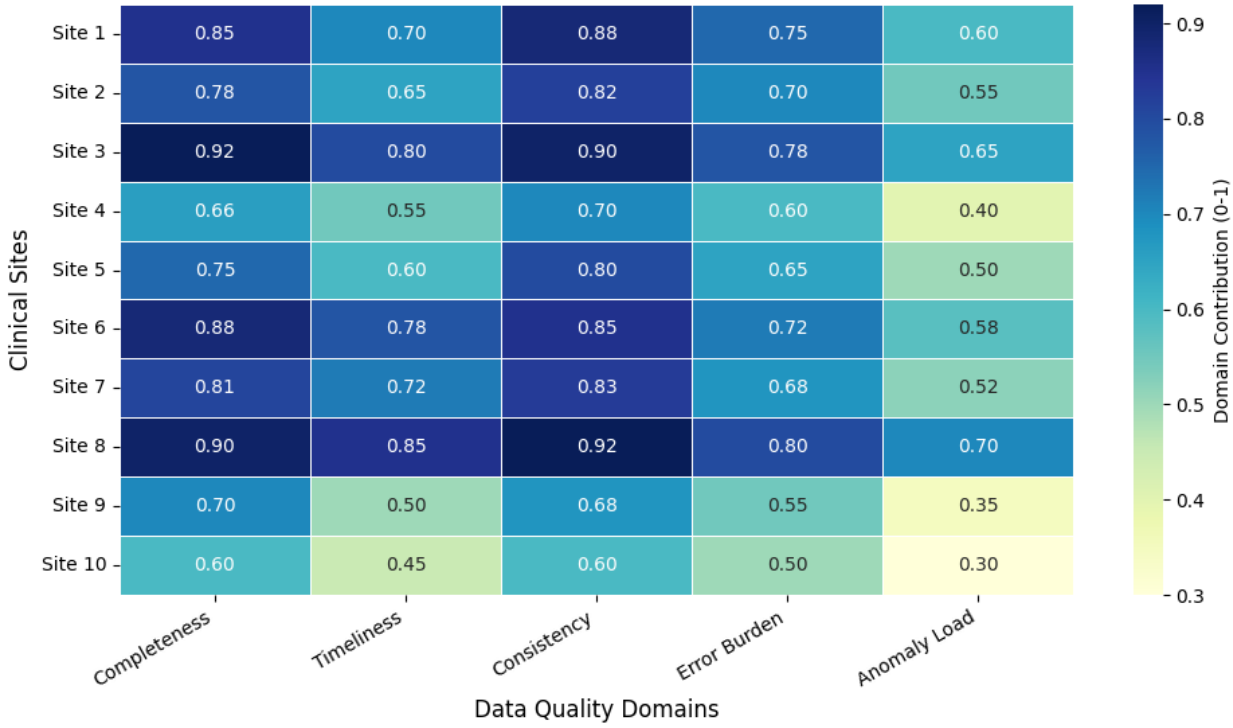
- Red cells indicate a site flagged as low-quality by the corresponding metric.
- CDIS captures all sites flagged by QR, ECPR, and AFD, plus additional sites not detected by any single metric.
- CBT, AFFIRM-AHF, and COORDINATE-Diabetes trials are grouped for cross-trial comparison.

4.5 Sensitivity Analyses

The quality of the CDIS composite was tested in two descriptive ways. Various domain weights, with the error burden contribution raised by 10 percentage points, produced slight shifts in site ranks, with the median ranking change per site an increment of a position. Three sites changed their integrity level status, indicating that CDIS is sensitive to the domain weighting and significant changes in the general rankings of websites. The systematic removal of one domain at a time showed that omitting timeliness resulted in the greatest change in composite rank, with five sites having their CDIS reduced. Removal of the anomaly load or consistency resulted in minor changes, suggesting that CDIS is stable to single-domain perturbations. Site-level

heatmaps (Figure 3) can also be used to assess the relative proportions of each domain in the composite score and identify sites where timeliness and completeness were the contributing factors with the most significant impact on low CDIS scores. The conclusions from these analyses are that the composite metric has been resilient to moderate changes in scoring methodology but sensitive to material differences in the quality of multi-domain data.

Figure 3 shows the Heatmap of CDIS domain contributions by site.



4.6 Key Findings

CDIS showed consistent and understandable responses across diverse settings in heterogeneous cardiovascular trials, with integrity patterns that were not evident with standard measures. The way it has provided a multidomain structure has allowed the identification of slight differences in completeness, timeliness, consistency, error burden, and anomaly load, showing how a loss of integrity is frequently caused by distributed interactions among people, reporting mechanisms, and digital interfaces. Bad checks in AE and SAE reporting, as evidenced by CDIS, were inconsistently reported in Query Rate and Edit-Check Pass Rate, particularly when manual confirmation and electronic data capture procedures overlapped. Cross-trial comparisons revealed consistent performance: the CBT trial website on the mobile platform showed performance variation related to asynchronous app submissions, AFFIRM-AHF indicated that classification drift was present in AE/SAE records, and COORDINATE-Diabetes pointed to lapses in integrating AE/SAE occurrences with medication records. The signals incorporated in a consolidated integrity profile by CDIS exhibited resilience to modification in weighting and domain structure. Altogether, the results make CDIS a valid analytic tool that can describe the behaviour of trial data across multisite digital infrastructures and provide a more inclusive picture of integrity than small-dimension indicators.

5. Discussion

CDIS offers a methodological rereading of data integrity in cardiovascular trials by conceptualising trial datasets as outputs of a distributed assemblage that comprises human judgment, digital platform structures, and algorithmic structuring. The classic signs, such as Query rate, Edit check pass rate, and audit finding density, capture only a single dimension of this assemblage (Habib et al., 2025). They are usually pegged to compliance with procedures and catch certain observable violations, such as missing fields or programmatic disparities. (David & Thomas, 2023; Javaid et al., 2022; Khan & Md Rasel, 2023). The findings of the research indicate that these measures provide limited visibility into the more detailed patterns that emerge in multisite clinical research, mainly when AE and SAE processes are based on mixed manual and electronic validation. CDIS attempts to overcome such limitations by incorporating domain signals into a compound site performance representation (Garcia et al., 2025; Young et al., 2025). The multidomain structure facilitates the detection of a drift in integrity based on the reporting cadence, event sequence, and relationship inconsistencies across the form and platform. The sites with marginal yet systematic AE/SAE discrepancies observed explain the occurrence of integrity failures as not merely due to the errors of a particular user but somewhat related to interactions over the course of use of the digital infrastructure (Khan & Md Rasel, 2023). This underscores the importance of data integrity as a practice shaped by the interaction among human documentation, software code, and system-level constraints.

Posthuman orientation is present in the working mechanism of CDIS: the score is not a detached overview but rather a computational process that interprets and orders data activities across locations (Cheremnykh & Gubanov, 2023; Clays et al., 2021). The confluent performance across three different cardiovascular trials highlights the ability of CDIS to scale diverse heterogeneous environments, such as the presence of app submissions in the mobile CBT trial, the presence of complex adjudication pathways in AFFIRM-AHF, and the presence of medication-event relationships in COORDINATE-Diabetes (Ponikowski et al., 2019; Tannu et al., 2024). By obtaining these variations without resorting to statistical testing, the CDIS demonstrates the ability to provide interpretive insights aligned with modern models of digital governance in clinical research (Ethan & Md Rasel, 2023; Johansen et al., 2025). The results also support the affirmation of data integrity as an epistemic and regulatory construct. In line with ICH E6(R2), CDIS anticipates the need for transparency, traceability, and reliability across distributed digital ecosystems (Cielemęcka & Daigle, 2019; FDA, 2019). The composite score serves as a mediating tool between regulatory expectations and real-time data behaviour, enabling the investigator and sponsor to visualise integrity across sites. Collectively, these results imply that CDIS provides a scalable, theoretically sound method of analysing the trial-based data as a dynamically interacting system of human and algorithmic factors (Elgin & Elgin, 2024). The fact that it can model behaviour across multiple domains, discover loopholes that traditional metrics have not recognised, and hold steady under changing weighting arrangements makes it a valuable tool for monitoring multisite cardiovascular studies. The argument emphasises the importance of CDIS not as an indicator but as a model for understanding the relational processes that define data integrity in modern clinical trials.

5.1 Implications for Clinical Trials

The CDIS framework offers a multidimensional, standardised measure of data integrity that complements conventional quality metrics. By integrating completeness, timeliness, consistency, error burden, and anomaly detection, CDIS provides actionable insights for trial monitoring, potentially reducing protocol deviations, improving AE/SAE reporting fidelity, and enhancing the reliability of primary and secondary endpoint analyses (Saleh Moussa et al., 2025). Adoption

of CDIS could improve trial efficiency, reduce the need for extensive site audits, and strengthen confidence in study conclusions. Its scalability across trial phases and diverse study designs positions CDIS as a potential standard metric for both cardiovascular research and broader clinical trial applications.

5.2. Limitations

CDIS performance depends on structured site-level data, and non-standardized reporting may require pre-processing or imputation, introducing potential bias. It has been validated in only three cardiovascular studies, limiting its applicability to other disease areas, decentralized trial designs, or adaptive trials. Implementing CDIS requires a computational platform and integration with existing data management systems, which could be challenging for smaller trial networks. Furthermore, CDIS evaluates multi-domain issues but does not measure the clinical validity or interpretability of individual outcomes. As a result, it focuses on data quality rather than the clinical relevance or accuracy of specific trial endpoints.

6. Conclusion

The validation of CDIS across three completed cardiovascular trials demonstrates its value as a multidimensional, standardised measure of clinical trial data quality. By integrating completeness, timeliness, consistency, error burden, and anomaly load, CDIS identified low-performing sites that conventional metrics alone failed to capture. The framework proved robust to moderate variations in domain weighting and single-domain exclusion, supporting its reliability across heterogeneous trial designs and patient populations. Implementing CDIS can directly improve trial oversight by highlighting sites that require targeted data quality interventions, thereby enhancing the fidelity of AE/SAE reporting, endpoint accuracy, and overall trial integrity. This adds to the view that clinical trial data cannot be interpreted merely as information stored, but rather as a human-machine assemblage in which infrastructure, software logic, reporting rates and regimes, and regulator expectations are produced in mutuality to create the conditions of integrity. The ability to aggregate multi-domain information into a single composite score provides a scalable and actionable tool for investigators, monitors, and regulatory reviewers. Looking forward, adoption of CDIS as a standard metric across cardiovascular research and potentially other therapeutic areas could facilitate automated monitoring, promote harmonised data quality benchmarks, and reduce the reliance on resource-intensive audits. The results of its use across three heterogeneous cardiovascular datasets demonstrate that it can enhance the role of digital governance and inform the development of future clinical research infrastructures. With the diverse modernisation of trial environments, including greater automation, mobile interfaces, and decentralised reporting, data on data integrity enacted and maintained across distributed clinical systems would require tools like CDIS.

7. Future Research Directions

Three areas should be the subject of further research. To begin with, CDIS scoring in electronic data capture systems would be automated, enabling early detection and real-time tracking of data quality issues. Further, multi-therapeutic applications (e.g., cancer trials, endocrinology) would validate it and define its broader applicability and potential standardisation (Reurean-Pintilei et al., 2024; Zeng et al., 2025). In addition, site-level interactive dashboards to support a specific remediation plan and continuing quality control might be developed (Uthman et al., 2025; Young et al., 2025). Besides, more precise control over weighting schemes to indicate isolated trial priorities and the incorporation of CDIS into regulatory reporting standards can increase its

practical utility.

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