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Data interoperability and accounting information quality: A conceptual model, hypotheses and managerial implications

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Abstract
This study develops a conceptual model of the relationship between the data interoperability level (DIL) and accounting information quality (AIQ), with accounting data quality (ADQ) serving as an indirect channel and data governance maturity (DGM) acting as a moderating variable. Drawing on organizational information processing theory, the task-technology fit principle, and the complementarity perspective, DIL is defined along three technical, semantic, and process dimensions at the level of accounting processes. Five hypotheses are proposed: DIL influences ADQ (H1), ADQ influences AIQ (H2), DIL directly influences AIQ (H3), ADQ acts as a mediator (H4), and DGM moderates the DIL–ADQ relationship (H5). The study proposes measurement methods and a verification plan, the hypotheses have not yet been tested by using data.

Keywords: Data interoperability, accounting information quality, accounting data quality, data governance, accounting information systems

Introduction

Accounting information is derived from data originating from various departments and applications; however, the mere fact that these applications operate concurrently does not guarantee that the data exchanged is interpreted consistently. (Chen *et al*., 2008; Petrasch & Petrasch, 2022; Vernadat, 2010) [9, 31, 35]. The question is how interoperability affects accounting information quality.

In Vietnam, the number of points where accounting data is exchanged with external parties is on the rise: electronic invoices facilitate the connection of purchase and sales data with tax authorities (Government, 2020) [10]; under the Law on Social Insurance No. 41/2024 [33]/QH15, participants are provided with monthly social insurance contribution information via electronic means (National Assembly, 2024a) [33], necessitating that payroll fund figures align with data held by social insurance authorities; and the Law on Data No. 60/2024 [33]/QH15 expands the scope for data connectivity and sharing (National Assembly, 2024b) [33]. In line with the roadmap for adopting International Financial Reporting Standards (Ministry of Finance, 2020) [6], these requirements place greater emphasis on data consistency and verifiability.

Accounting studies has linked the integration of information systems with management control (Chapman & Kihn, 2009) [8], system quality with management accounting data quality (Knauer *et al*., 2020) [23], and accounting information system quality (AIS) with accounting information quality (Nguyen & Nguyen, 2024) [30]. However, integration is only one component of system quality (Nelson *et al*., 2005) [29], and organizational conditions which alter the effectiveness of technical solutions (Weber *et al*., 2009) [38] have not been incorporated into the model.

The study addresses two questions: (RQ1) how does data interoperability relate to the accounting information quality; (RQ2) how does data governance alter the relationship between interoperability and data quality? The unit of analysis is the accounting process.

The study contributes a three-dimensional definition of DIL, five substantiated hypotheses, and a plan for empirical testing.

Theoretical Basis and Literature Review

1. Theoretical basis

Organizational information processing theory According to Galbraith (1974) [14], the greater the uncertainty and interdependence of tasks are, the larger the volume of information to be processed is; organizations respond by either reducing the need for information or increasing their capacity to process it. The theory has been applied at the organizational unit level, such as at the factory level when evaluating ERP (Gattiker & Goodhue, 2005) [15], and can therefore be applied to the level of accounting processes. DIL is considered a cross-system information processing capability: the received data is used immediately, without the need for further interpretation.

The task-technology fit theory (Goodhue & Thompson, 1995) [16], originally developed at the individual level, is applied here based solely on the logic of fit: the value of interoperability depends on the compatibility of the exchanged data with accounting requirements. The role of organizational conditions is explained through the perspective of complementarity: the value of information technology resources, at both the process and organizational levels, depends on complementary organizational resources (Melville *et al*., 2004) [28], including data governance.

The DeLone–McLean model and the perspective of data quality based on intended use help define the structure: DeLone and McLean (2003) [12] distinguish between system quality and information quality; Wang and Strong (1996) [37] categorize data quality attributes into intrinsic, contextual, representational, and accessibility-related groups.

2. Key concepts

Data Interoperability Level (DIL). Enterprise interoperability concerns the interaction between systems across three technical, semantic, and organizational layers

(Chen *et al*., 2008; Vernadat, 2010) [9, 35], wherein data formats and meanings must be preserved and understood consistently (European Commission, 2017) [13]. DIL refers to the extent to which systems exchange, receive, and reuse data with compatible structures and meanings within a defined accounting process; it encompasses three dimensions: *technical* (automated transfer using appropriate formats and protocols), *semantic* (standardized category codes, units of measurement, business statuses, and recording timestamps, including the use of shared master data), and *process* (exchange cadence and sequence aligned with accounting processes). DIL encompasses interactions with tax authorities, social security agencies, and banks as data enters the process; at these points, standards are externally mandated - much like XBRL (Baldwin *et al*., 2006) [3] - meaning that DIL reflects the capability for standard ingestion and mapping. The number of software applications or the presence of an enterprise resource planning (ERP) system does not represent DIL.

Accounting data quality (ADQ) refers to the extent to which input data meets the processing requirements of a given process, encompassing accuracy, completeness, consistency, and timeliness (Wang & Strong, 1996) [37]. Accounting information quality (AIQ) refers to the extent to which the information outputs of a process, that is, the set of data and the manner in which it is presented (for example, revenue line items and their related disclosures, or internal revenue reports), meet the requirements of the users. The International Accounting Standards Board (IASB, 2018) [20] identifies two fundamental qualitative characteristics (relevance and faithful representation) and four enhancing qualitative characteristics (comparability, verifiability, timeliness, and understandability); these characteristics apply to the aforementioned set of data, with comparability considered across different periods.

Data Governance Maturity (DGM) refers to the extent to which an organization has established and implemented operational control mechanisms for its data: ownership and accountability, quality oversight, reconciliation, exception handling, delegation of authority, change tracking, and training (Abraham *et al*., 2019; Khatri & Brown, 2010; Weber *et al*., 2009) [1, 22, 38]. Master data standards belong to the semantic dimension of DIL. “Maturity” is understood as the degree of institutionalization, measured on a continuous scale.

Table 1: Distinguishing between DIL, ADQ, AIQ, and DGM

Concept	Subject of evaluation	Measurement questions	Common pitfalls
DIL	Channels and processes for data exchange among systems, including those involving tax authorities, insurance providers, and banks	Do the data retain their structure and business meaning as they move through the systems?	Aligning DIL with the number of software instances or the presence of ERP
ADQ	Records and input data for the accounting process	Is the data accurate, complete, consistent, and timely when it enters the processing stage?	Aligning raw data with reports
AIQ	Process output data set for defined-users	Is the information relevant, honest, comparable, verifiable, timely, and easy to understand?	Trace any errors in the report back to the source data
DGM	Operational control mechanisms for data	Are discrepancies detected and addressed, and is there someone held accountable?	Combined with DIL (as a master data standard) or with AIQ verification capabilities

Source: Compiled by the authors.

For ADQ, timeliness means data arrives before the processing deadline; for AIQ, it means information remains valuable for decision-making. Consistency in ADQ refers to alignment across systems.

3. Research overview and gaps

Table 2 summarizes relevant studies. The quality of the information system is positively related to the quality of management accounting data ($\beta = 0.33$; $p < 0.01$), whereas the diversity of data sources is negatively related to the quality of the system (Knauer *et al*., 2020) [23]. In Vietnam, AIS quality is typically measured as a multi-dimensional structure (Vu *et al*., 2020) and has a positive impact on AIQ (Nguyen & Nguyen, 2024) [30].

ERP integration does not automatically generate unified information for control purposes (Dechow & Mouritsen, 2005) [11], while research on digital transformation highlights the mediating role of accounting information system (AIS) quality and data quality (Bal *et al*., 2026; Barani & Asiaei, 2026) [2, 4].

Table 2: Synthesis of related research and research gaps

Research contents	Author (year)	Method	Key results	Gap
Enterprise interoperability	Chen *et al*. (2008); Vernadat (2010) [9, 35]	Analysis of the concept	Distinguishing between the technical, semantic, and organizational layers	Not yet integrated with accounting
Data integration at the technical layer	Petrasch & Petrasch (2022); Heguy *et al*. (2024) [18, 31]	Based on a model; an extension of BPMN 2.0, FMECA	Identifying incompatibilities; Ranking data exchanges by criticality level	Beyond accounting
System integration and control	Chapman & Kihn (2009); Dechow & Mouritsen (2005) [8, 11]	Survey of 169 managers, PLS; case study	Integration is linked to enabling control; integration via ERP is only partially achieved.	Do not measure information quality
Quality of management accounting systems and data	Knauer *et al*. (2020) [23]	Survey of 143 German enterprises; SEM	System quality is positively related to data quality; the variety of contact sources is negatively related to system quality.	System quality is a broad construct.

System quality components	Nelson *et al*. (2005) [29]	Experiments, data warehouse	Integration is a component of system quality.	Beyond accounting
AIS data quality	Xu (2015)	Cognition-based experimentation	Leadership commitment, system characteristics, and input controls are positively related to data quality.	Not yet considered the data–information relationship
AIS and AIQ Quality	Nguyen & Nguyen (2024); Vu *et al*. (2020) [30, 36]	Survey of small and medium-sized enterprises in Vietnam	AIS quality is measured across multiple dimensions; it has a positive impact on AIQ.	Broad structure; not separate interoperability
Digital transformation, AIS quality, and data	Barani & Asiaei (2026); Bal *et al*. (2026) [2, 4]	PLS-SEM in Iran; mixed-use design in Morocco	AIS quality and data quality as mediators for financial outcomes	Not considering interoperability
Data governance	Khatri & Brown (2010); Weber *et al*. (2009); Abraham *et al*. (2019) [1, 22, 38]	Analysis of concepts; situations; overview	Decision domain; context-dependent design	Not yet linked to AIQ; not yet tested moderating variable
Data interoperability and governance	Cao & Iansiti (2023) [7]	U.S. Financial Group	Internal, standardized APIs facilitate compliance with data protection regulations	The result is not AIQ

Source: the authors compiled this from the cited works.

There has been no research that specifically examines the contribution of data interoperability to AIQ when separating from system quality and input data quality, or governance conditions might alter that contribution.

Research Methods

This is a conceptual study, specifically a model-building study, according to the classification by Jaakkola (2020) [21], that incorporates elements of theoretical synthesis. The relationships are presented as hypotheses, with an operationalization direction and a plan for verification.

The materials are selected purposefully based on their relevance to the structures, the ability to trace them back to their origins, and the sufficiency of information regarding their context, design, and outcomes; this information has been cross-referenced with the original records, with coverage extending up to October 2026. Each hypothesis is derived in three steps: identify the mechanism based on foundational theory, compare it against the most recent evidence, and outline the limitations of that evidence.

Research Model and Hypotheses

1. Data interoperability and accounting data quality

Data discrepancies often arise at the point of transfer: manual re-entry, mismatched codes, differences in recording timestamps, and lost or duplicate records. Technical interoperability reduces re-entry and the loss of records; semantic interoperability minimizes discrepancies in codes and units; and process interoperability narrows the gap between the timing of data generation and the timing of accounting entries. This argument aligns with analyses of incompatibilities in data integration (Heguy *et al*., 2024; Petrasch & Petrasch, 2022) [18, 31] and with the positive relationship between system quality including integration and data quality (Knauer *et al*., 2020; Nelson *et al*., 2005) [23, 29]. The impact is expected to be more evident in terms of consistency, completeness, and timeliness, rather than accuracy.

H1: Data interoperability level (DIL) is positively related to accounting data quality (ADQ) within a defined accounting process.

2. Data quality and accounting information quality

The quality of information products depends on the quality of the input data (Wang & Strong, 1996) [37]: missing, incorrect, or delayed data diminishes the faith, comparability, and timeliness of information. Xu (2015) and Nguyen and Nguyen (2024) [30, 39] record a positive relationship between two adjacent stages, but they do not directly test the ADQ–AIQ line. Since AIQ is also influenced by recording and presenting rules (IASB, 2018), accounting policy is included as a control variable.

H2: Accounting data quality (ADQ) is positively related to accounting information quality (AIQ) when the two structures are evaluated separately.

3. The remaining direct impact and the mediating role of ADQ

According to information-processing theory, the capacity to coordinate data sources helps address cross-departmental information tasks (Galbraith, 1974) [14]. The direct mechanism is the ability to link records across sources to generate new informational content that differs in quality from that of the individual records themselves. For instance, while order data and cost-of-goods data may each be accurate, complete, and timely, it remains impossible to calculate gross profit by sales channel if the sales system and the inventory system do not share a common transaction code. When interoperability enables connectivity, the appropriateness of information increases without any attributes of data quality (ADQ) changing, provided that the new content meets the users' requirements (Goodhue & Thompson, 1995) [16]. Given that the evidence is merely suggestive (Chapman & Kihn, 2009) [8], H3 is tested as a remaining direct effect after accounting for ADQ.

H3: Data interoperability level (DIL) has a direct positive relationship with accounting information quality (AIQ) when simultaneously considering accounting data quality (ADQ).

Based on H1 and H2, DIL can influence AIQ through ADQ, which is analogous to the mediating role of AIS quality and data quality as observed in studies on digital transformation (Bal *et al*., 2026; Barani & Asiaei, 2026) [2, 4]. If both the indirect and direct effects are significant, ADQ is a partial mediator.

H4: Accounting data quality (ADQ) mediates the relationship between data interoperability level (DIL) and accounting information quality (AIQ); The indirect effect DIL → ADQ → AIQ is positive.

4. The moderating role of data governance maturity levels

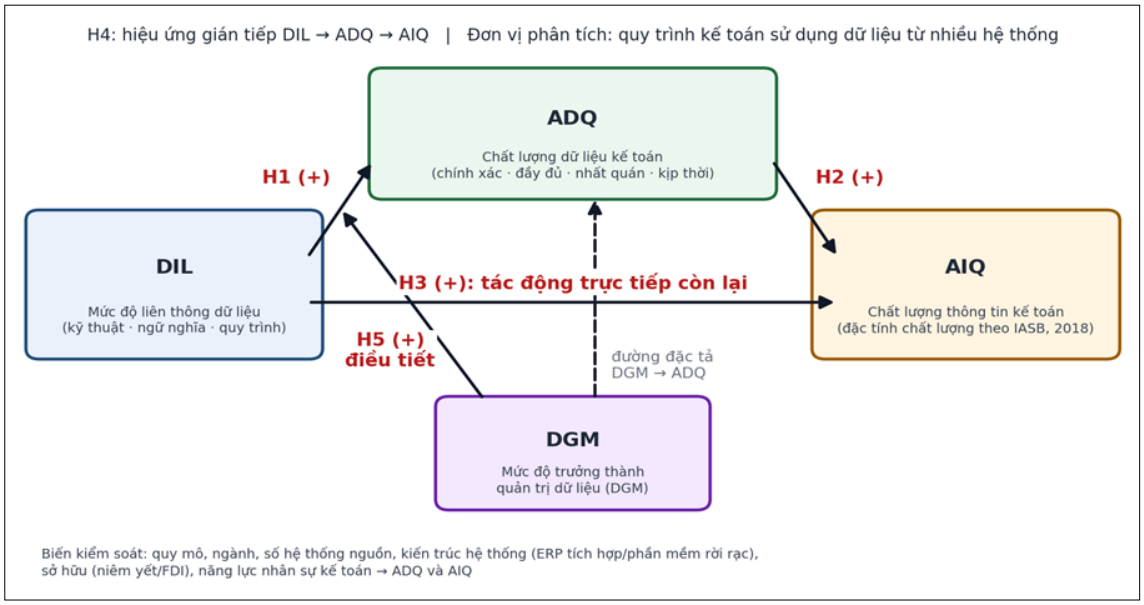
From a complementary perspective, the value of technological resources depends on concomitant

organizational resources (Melville *et al*., 2004) [28], and data governance design is context-dependent (Weber *et al*., 2009) [38]. DIL and DGM act at two different stages: DIL determines whether data passes through a transfer point without reinterpretation, while DGM determines whether any residual discrepancies are detected, attributed to a responsible party and addressed or not (Cao & Iansiti, 2023 [7]; Xu, 2015).

When DGM is high, the benefits of interoperability translate fully into data quality; when DGM is low, discrepancies originating at the source can spread to multiple systems without detection. Another specification is that DGM influences ADQ through DIL, as well-managed enterprises may invest more in interoperability. The study adopts a moderating role because DGM's mechanism lies in bias correction, and estimates alternative specifications for comparison (Section 5.2).

H5: Data governance maturity (DGM) positively moderates the relationship between data interoperability level (DIL) and accounting data quality (ADQ): the impact of DIL on ADQ is stronger when DGM is high.

5. Research model



Source: the group of authors proposes. Note: The H5 arrow points to the DIL → ADQ path; the dashed line DGM → ADQ represents the required specification path when estimating the interaction term.

Fig 1: Proposed research model

Operationalization and Validation

1. Operating the structures

Table 3 presents the operationalization approach. The observed variables utilize a Likert scale and are developed and validated in accordance with MacKenzie *et al*. (2011). According to Becker *et al*. (2012) [5], DIL, ADQ, and AIQ are reflective-formative second-order constructs, as their first-order dimensions are not interchangeable; DGM is a formative first-order construct.

Table 3: Operationalization of structures

Construct / dimension	Measurement content	Please avoid overlapping.
DIL – technique	Data is automatically transferred in a standard format, with no need for re-entry.	Does not mention/No mention of data errors (pertaining to ADQ)
DIL – semantics	Codes, units of measure, and statuses are consistently mapped, including against external standards; shared master data.	No mention of reconciliation and exception handling (pertaining to DGM)
DIL – process	The cadence and sequence of exchanges align with the accounting and closing schedule.	Distinguishing from the timeliness of ADQ and AIQ
ADQ	Accurate, complete, consistent, and timely; objective indicators (re-entry rates, reconciliation exceptions, late-arriving records)	The object is a record, not a report.
AIQ	Six characteristics according to the IASB (2018) [25] for the set of outputs from a process	Do not include usage results in the observed variables.
DGM	Data responsibility; monitoring, exception handling; reconciliation, access control, change logs; training	Excludes master data standards (pertaining to semantic DIL); does not overlap with AIQ verification criteria.
Control variable	Scale, industry, number of source systems, system architecture, ownership, and accounting personnel capabilities	The number of source systems reflects a variety of data sources (Knauer *et al*., 2020) [23]

Source: the group of authors proposes.

2. Design and analysis

An analytical unit is an accounting process that generates a specific set of data (for example, the sales-to-revenue-recognition cycle). The framework prioritizes medium and large enterprises, where roles are clearly separated; consequently, the results cannot be generalized to small

businesses. The person in charge of the information system assesses DIL; the chief accountant assesses ADQ; users of the output data or internal audit assess AIQ; DGM is addressed by both departments. ADQ is supplemented by objective indicators derived from the system (re-entry record rate, reconciliation exceptions, and late-arriving entry). When three sources are not available, ADQ and AIQ are measured at two points in time; common method biases are assessed by using a marker variable and the full-collinearity VIF (Kock, 2015; Podsakoff *et al*., 2003) [24, 32].

With a minimum path coefficient of 0.20, a significance level of 5%, and a power of 80%, the inverse square root method yields a sample size of approximately 155 (Kock & Hadaya, 2018) [25]; for an interaction coefficient of 0.10, a sample size of approximately 620 is required. The sample size for H5 should therefore be determined by using Monte Carlo simulation on the full model.

The model was estimated using PLS-SEM due to the presence of a formative higher-order structure and interaction terms; the higher-order structure was constructed following a two-stage approach (Becker *et al*., 2012) [5], and the interaction terms were generated from latent variable scores. Discriminant validity is assessed using HTMT (Henseler *et al*., 2015) [19]. H1–H3 are evaluated by using path coefficients and bootstrap confidence intervals; H4 via indirect effects (Zhao *et al*., 2010) [40]; and H5 through interaction coefficients and the index of moderated mediation (Hayes, 2015) [17]. An alternative model DGM → DIL → ADQ is estimated for comparison; a supplementary analysis is examined each dimension of DIL in relation to each attribute of ADQ. Given the cross-sectional nature of the data (Maxwell & Cole, 2007) [27], the results regarding H4 should not be interpreted as a causal relationship.

Discussion and Implications

1. Expected theoretical contributions

The model makes three theoretical contributions: DIL is defined as a three-dimensional capability at the process level, distinct from system quality, data quality, and data governance. A distinction is made between direct pathways (linking records to create new content) and indirect pathways (mediated by ADQ). Furthermore, data governance is viewed as a complementary resource, implying that the returns on investment in interoperability vary according to the level of data governance maturity (DGM) (Melville *et al*., 2004; Weber *et al*., 2009) [28, 38].

2. Managerial implications

The following implications are derived from the model and require verification.

Table 4: Managerial implications and basis in the model

Implication	Basis in the model
Assess interoperability based on business processes and data semantics; establish a catalogue of codes and common mapping rules (European Commission, 2017) [13]	Semantics, technical DIL; H1
Prioritize handover points that have a significant impact on the closing process (revenue, cash, payroll/insurance, and invoices/taxes), ranked by their level of criticality (Heguy *et al*., 2024) [18].	DIL Process; H1, H3
Establish data accountability, reconcile source data against ledgers, manage access permissions, and handle exceptions all while enhancing interoperability.	DGM; H5
Specifically monitor the following metrics: DIL, ADQ (missing mandatory fields, duplicate records, late-arriving data), and AIQ.	H1–H4
Evaluate each dimension of DIL individually before expanding connectivity; the priority order among these dimensions requires validation.	A number of source systems; additional analysis

Source: compiled by the authors.

For the external data exchange points mentioned in section 1, enterprises should consider semantic standardization and data governance as prerequisites when investing in connectivity.

Limitations and Directions for Future Research

The research has limitations: the relationships are hypothesized; the overview is selective; the three dimensions of DIL and the characteristics of AIQ at the process level require validation; the model does not account for leadership support, the level of automation, or non-linear relationships; and the inverse relationship between DGM and DIL has only been examined via an alternative model using cross-sectional data.

Future research directions include validating the scales, testing hypotheses H1–H5 as well as alternative models, comparing the effects of the three dimensions of DIL, and employing longitudinal data or conduct a case study to clarify the mechanism.

Conclusion

The study proposes a model in which data interoperability influences the quality of accounting information both directly and indirectly through data quality, while data governance, acting as a supplementary resource, moderates the impact of interoperability on data quality. The five hypotheses, alternative models, and testing plan serve as the foundation for subsequent empirical research.

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