Data governance maturity and employee perception of business intelligence in selected fintech firms in Nigeria: The mediating role of data quality

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Abstract

Purpose: This study examined whether data governance maturity (DGM) predicts employee perception of business intelligence performance (EPBI) in selected fintech firms in Nigeria, the mediating role of data quality (DQ).

Design/methodology/approach: A survey of 342 employees from Nigerian fintech firms across data/analytics, IT, compliance, and management was conducted. SEM in AMOS tested hypothesised paths using maximum likelihood and 5,000 bootstrap samples.

Findings: DGM positively predicted DQ and DQ positively predicted EPBI. The indirect effect of DGM on EPBI through DQ was statistically significant and consistent with full mediation. DGM explained forty-eight percent of the variance in DQ, whilst DQ accounted for thirty-eight percent of the variance in EPBI.

Limitations and Research implications: The cross-sectional research design constrains causal inference, and restricting the sample to Nigerian fintech organisations limits broad generalisability. Future work should deploy longitudinal designs and multi-country samples across other African fintech markets.

Practical Implications: Fintech organisations aiming to improve how employees perceive and utilise BI systems must treat data governance as a strategic capability rather than a regulatory formality. Governing data well is the antecedent through which data quality, and eventually employee BI performance perception, is achieved.

Originality/value: This study is among the first to empirically model the DGM-DQ-EPBI pathway in the Nigerian fintech sector, extending information quality theory and the resource-based view to a high-growth, data-intensive, African financial services context.

Keywords: Data Governance Maturity, Employee Perception of Business Intelligence, Data Quality, Fintech, Information Quality, Technology.

Introduction

Nigeria’s financial technology sector has moved from the periphery of the country's financial system to its operational centre within a single decade. Fintech firms now process the majority of retail electronic transactions, serve credit markets that conventional banks have historically neglected, and accumulate transactional and behavioural data at a scale that legacy institutions are only beginning to approach (Akinlade et al., 2026; Kolawole et al., 2024). Yet

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data volume alone confers no advantage. Translating that data into reliable decision-support intelligence requires an organisational foundation, specifically mature governance of data assets and the quality of those governance structures sustained, which a considerable proportion of Nigerian fintech operators have not yet built. Business sustainability in a data-driven financial services context depends, in no small part, on precisely this capacity (Adeyemi et al., 2026; Ahmed & Gad-Elrab, 2021; Samsø Fibæk et al., 2021).

Data Governance Theory and the Information Quality Management Framework jointly underpin this study's theoretical architecture. Abraham et al. (2019) positioned governance design as the organisational function that determines whether data practices are coherent, accountable, and capable of producing reliable outputs, a position Marcucci et al. (2023) corroborated across multiple industries by confirming that governance quality exerts a measurable upstream influence on data quality outcomes. Dahlberg and Nokkala (2015) refined this argument through agency theory, showing that governance maturity functions as an incentive-alignment mechanism that brings data producers, stewards, and consumers into a shared accountability structure. The IQM Framework, as Kankam et al. (2023) and Olszak and Ziemba (2006) articulated it, treats data quality not as a dataset attribute but as an emergent product of the procedures and standards applied throughout the data lifecycle, a position America (2025) extended by demonstrating that formalised quality management disciplines produce measurable gains in data accuracy and governance compliance. Together, these frameworks generate the study's central proposition: governance maturity creates the structural preconditions for data quality, and data quality in turn determines the reliability of business intelligence outputs, a mediated chain supported in developed-economy contexts (Bližnák et al., 2024; Merkus et al., 2025) but untested within the Nigerian fintech sector.

The governance challenges this study examines resonate well beyond the Nigerian context. In Indonesia, Fattah et al. (2025) found that formalised open data governance in public sector organisations measurably improves institutional transparency and operational performance, whilst Yulyanti et al. (2023) writing in this journal, demonstrated that institutional governance variables exert a statistically significant influence on financial sector performance outcomes, confirming that governance quality functions as an upstream determinant of analytical reliability across financial services contexts. Malaysia presents a comparable trajectory, in which Bank Negara Malaysia and the Securities Commission have progressively tightened data governance obligations on licensed fintech operators, driven by the recognition that consistent performance in data-intensive financial firms cannot be sustained without mature governance foundations. Saka et al. (2025) also published in this journal, further established that structured governance evaluation frameworks yield decision-relevant insights across varied institutional environments, a finding whose methodological logic aligns directly with the structural modelling approach adopted here. Across these Asian contexts, the pattern is consistent: where governance formalisation is weak or uneven, financial sector performance outcomes follow suit. It is precisely this relationship that the present study subjects to empirical scrutiny within the Nigerian fintech sector.

The critical gap is whether this chain of effects holds within technology-native financial firms operating in a developing-economy institutional environment. Nigeria's fintech sector is characterised by weaker regulatory enforcement capacity, less established data management benchmarks, and an industry that has scaled considerably faster than the governance norms designed to discipline it. Institutional voids of this kind do not merely slow the adoption of governance; they alter the conditions under which governance mechanisms take effect. The Nigeria Data Protection Act Isibor (2024) and the CBN Risk-Based Cybersecurity Framework Nnaji (2026) impose specific data management obligations on licensed operators, yet assessments by the Nigeria Data Protection Commission have consistently found material deficiencies in data classification, access control, and metadata stewardship across the sector (Adelusi et al., 2023). Previous studies of business intelligence performance in Nigeria have foregrounded technology readiness and managerial support as antecedents (Adewusi et al., 2024; Ahmed & Gad-Elrab, 2021; Hmoud et al., 2023), whilst data governance research in Nigerian financial services has concentrated on conventional commercial banks rather than technology-native firms (Bernardo et al., 2024; Komolafe et al., 2024; Merkus et al., 2023). No published study has modelled the DGM-DQ-EPBI chain within Nigerian fintech firms using structural equation modelling. Saka et al. (2025) and Yulyanti et al. (2023) demonstrated that governance frameworks produce performance-relevant effects across varied institutional contexts, including in Asian financial markets that face analogous regulatory challenges; however, neither study modelled data quality as an explicit mediating mechanism, nor did either examine a technology-native financial sector. Adewusi et al. (2024) examined BI performance antecedents in Nigeria but did not incorporate a governance construct, whilst Komolafe et al. (2024) examined data management capability and firm performance without testing a mediated structural pathway. Where prior Nigerian work has therefore isolated either the governance side or the BI-performance side of this chain, and prior cross-country governance work has not tested the mediating mechanism, this study is the first to model the full DGM-DQ-EPBI pathway simultaneously, within a single technology-native, data-intensive sector. This is the specific contribution this study extends to the Nigerian fintech context.

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The study makes three contributions. It tests the direct effect of DGM on EPBI performance within Nigerian fintech firms; it examines Data Quality as a mediating variable in that relationship; and it models both pathways simultaneously using Covariance-Based Structural Equation Modelling on a sample of 342 professionals drawn from CBN-licenced operators. Theoretically, it extends the DGM-DQ-BI framework to an emerging-market setting in which institutional conditions differ from those under which the framework was first validated. Practically, the findings offer actionable evidence for governance practitioners and regulators in Nigeria and in comparable Asian digital financial services markets.

Therefore, the study examines the impact of data governance maturity and employees' perceptions of business intelligence in selected fintech firms in Nigeria to answer the following question: *RQ1:* What is the effect of data governance maturity on data quality? *RQ2:* Does data quality affect employee perception of business intelligence performance? and *RQ3:* What is the indirect influence of data governance maturity on employee perception of business intelligence performance through data quality?

Literature Review

Conceptual Review

Data Governance Maturity

The term 'data governance maturity' does not represent a single condition but rather a trend. At its lower end, data is managed ad hoc, decisions concerning data are made informally, and accountability is diffused. At its top end, governance is institutionalised: there are formal stewardship positions, established rules, enterprise-wide standards, and continuous improvement techniques applied to data management procedures throughout their lifecycle. This evolution is evident in the maturity model literature (Pörtner et al., 2025), which draws on capability maturity models originally developed in software engineering and later extended to data management by organizations such as DAMA International.

Abraham et al. (2019), whose paradigm remains one of the most quoted in data governance research, structure the governance design space around five decision domains: data principles, data quality standards, metadata management, data access, and lifecycle management. The maturity of a firm's governance architecture is measured by how methodically it has built, assigned, and enforced decision rights across each of these domains. Bližnák et al. (2024), in a systematic review of data governance literature published between 2017 and 2023, confirmed that this multi-domain understanding has become the

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dominant conceptualisation in both academic and practitioner communities, though operationalisation varies considerably across studies.

For Nigerian fintech enterprises, governance maturity holds a dual relevance. It is simultaneously a compliance need, given the data management duties under the Nigeria Data Protection Act (2023), and a competitive competence. Firms that regulate data effectively are better positioned to create trustworthy analytical results, preserve consumer trust, and respond efficiently to CBN regulatory returns. Merkus et al. (2025) demonstrated, in a multi-case study of large organisations, that firms with formally validated governance capabilities reported consistently higher perceptions of usefulness and ease of use in their data systems than those without, suggesting that governance maturity creates value at the point of data consumption as well as at the point of data production.

Data Quality

Data quality is not a single feature but a collection of properties that, examined collectively, decide if data is fit for the purpose to which it is employed (Alzahim et al., 2026; Ameria, 2025). Bernardo et al. (2024), who categorised quality attributes into intrinsic, contextual, representational, and accessibility categories, remains the most generally accepted definition of the term in information systems research. More recent research has tended to focus on four operationally significant dimensions: accuracy, completeness, consistency, and timeliness, each of which has demonstrable ramifications for downstream analytical procedures.

In the fintech business, the repercussions of poor data quality are distinct and substantial. Inaccurate client identity records expose companies to fraud. Transaction logs with missing information stop reconciliation procedures and cause audit trail gaps. Inconsistent data formats across system levels, particularly where historical infrastructure coexists with new API-driven platforms, create integration issues that BI solutions cannot silently resolve. Saputra et al. (2023) showed that the relationship between quality and performance is not direct but is mediated through user perceptions of system usefulness; a finding that points to the importance of measuring quality not just at the data layer but at the point of decision use. Kankam et al. (2023), examining information quality in supply chain settings, found that information sharing fully mediated the quality-performance link, suggesting that the channel through which quality effects reach performance outcomes is context-dependent, a point with direct implications for the mediation model tested here.

The special problem facing Nigerian fintech data quality is the coexistence of multiple data sources: mobile money platforms, USSD channels, web-based applications, and partner bank feeds, each providing data in diverse formats and with varying latency profiles. Managing quality across these diverse sources is qualitatively different from managing quality in a single-system scenario, and it elevates the role of formal governance structures as the mechanism for the consistent development and application of quality standards (Ameria, 2025).

Employee Perception of Business Intelligence Performance

Employee Perception of Business Intelligence performance, as this study uses the term, refers to the degree to which an organisation’s BI systems and procedures produce outputs that are accurate, timely, relevant, and capable of meaningfully supporting users' decisions. This operational definition is consistent with the treatment in Adewusi et al. (2024), whose review of BI in the big data era argued that BI value is realised not at the point of data storage or processing but at the point of decision use, and that the quality of the analytical outputs is the most direct determinant of that realised value.

For Nigerian fintech organisations, BI performance has both regulatory and commercial dimensions. The CBN and FRCN necessitate extensive quarterly reporting on credit risk, transaction volumes, and customer data handling; all of which depend on sound analytical systems. Komolafe et al. (2024), in a study of digital financial services and bank performance in Nigeria, identified data-driven decision-making as a critical differentiator among high-performing digital banks, noting that firms with more mature analytical capabilities achieved significantly better return metrics. Shittu et al. (2024) similarly demonstrated, across a healthcare context, that BI tool quality had a significant independent effect on operational outcomes, supporting the view that BI performance is not merely a technical variable but an organisational capability with direct performance consequences.

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Theoretical Review

Data Governance Theory

The theoretical case for treating governance as the primary antecedent of data quality and downstream informational performance rests on the argument that data assets, like financial or physical assets, require formal decision rights, stewardship accountability, and process controls to generate value. Abraham et al. (2019) most comprehensively described this viewpoint, defining governance design as the meta-level activity that determines whether an organisation's data practices are coherent, consistent, and capable of change over time. Marcucci et al. (2023) examining data governance frameworks at the international policy level, confirmed that governance design strongly affects data quality outcomes across industries and country settings, providing cross-contextual support for the governance-as-antecedent argument.

Dahlberg and Nokkala (2015) mentioned that framework for corporate data governance integrated agency theory with data stewardship concepts, argued that the central challenge in data governance is aligning the incentives of data producers, data stewards, and data consumers so that quality is treated as a shared organisational responsibility rather than a technical by-product. This alignment argument is directly relevant to the Nigerian fintech context, where data is produced by distributed mobile and digital channels and consumed by centralised BI platforms, creating a natural tension between the organisational actors responsible for data capture and those who depend on the quality of that data for analytical outputs. Governance maturity, in this account, is the mechanism by which that tension is controlled.

Information Quality Management Framework

The Information Quality Management (IQM) Framework treats quality not as an attribute of datasets but as an emergent product of the procedures, responsibilities, and standards that govern how data are created, managed, and consumed. (Alzahim et al., 2026; Kankam et al., 2023; Olszak & Ziemba, 2006) definition positioned quality management as a continuous cycle of measurement, root cause analysis, improvement, and monitoring applied at every point in the data-creation pipeline. Ameria (2025) updated this perspective for the artificial intelligence era, arguing that integrating AI-driven quality monitoring with master data management disciplines produces measurable improvements in both data accuracy and governance compliance, pointing to the continued relevance of the IQM cycle even as the technical environment in which it operates changes rapidly.

Applied to the present inquiry, the IQM Framework provides the theoretical framework for interpreting data quality as a mediating variable rather than an independent one. Governance maturity creates the structural prerequisites for quality management, quality management produces high-quality data, and high-quality data generates great BI outputs. The framework

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also supports the multi-dimensional assessment of DQ employed in this study, in keeping with the notion that quality is not a unidimensional concept and that different quality dimensions carry varying weights depending on the analytical context in which the data is used.

Empirical Review

The relationship between data governance, data quality, and BI performance has attracted growing empirical attention over the past several years, though much of this work has focused on developed-economy contexts or on large multi-sector samples that do not specifically address fintech or developing market conditions.

Hmoud et al. (2023) examining BI adoption in Jordanian higher education institutions using PLS-SEM and a Technology-Organisation-Environment (TOE) framework, found that information quality was among the most significant determinants of BI adoption, with an effect exceeding those of technology infrastructure and vendor quality in several of their model specifications. Information culture emerged as the strongest overall predictor in their research, a conclusion that aligns with the governance culture thesis in the present study. Bany Mohammed et al, (2024), in a study of BI and analytics usage in the banking sector, showed that perceived analytical quality was the key driver of continuous BI use, suggesting that quality supports not just early acceptance but enduring organisational involvement with BI systems.

On the governance side, Bližnák et al. (2024) identified, through their systematic review, a consistent pattern across recent literature: organisations that have invested in formal governance structures, including data ownership frameworks, metadata management processes, and data stewardship roles, consistently report better data quality outcomes than those that manage data informally. Merkus et al. (2025) validated a data governance capabilities model across large organisations and found that governance capability profiles strongly correlated with data quality perceptions at the practitioner level, providing empirical support for the theoretical argument that governance is an antecedent of quality rather than a correlate. In the Nigerian and broader African context, Komolafe et al. (2024) found that digital financial services firms with stronger data management capabilities significantly outperformed their peers on key financial metrics, a finding that indirectly supports the governance-performance chain proposed here. Adeyemi et al. (2025) studying fintech firms in West Africa, argued that Extract, Transform, Load (ETL) tool sophistication, which depends heavily on underlying data governance structures for its effectiveness, was strongly associated with competitive advantage, further connecting data management maturity to performance outcomes.

Regarding the mediating role of data quality, Kankam et al. (2023) conducted one of the most immediately applicable evaluations of a quality-as-mediator model in their supply chain analysis, confirming that information quality affected performance outcomes through information sharing. Saputra et al. (2023) similarly found that the relationship between system and information quality and job performance operated through user perceptions, confirming that quality effects on performance are rarely direct but are instead mediated by the conditions that translate quality into usable analytical outputs. Adeyemi et al. (2025) studying self-service BI and customer satisfaction, found that the capacity of non-technical users to extract value from BI systems was significantly moderated by the quality of underlying data, reinforcing the argument that quality is a precondition for BI performance rather than a separate concern. Aldalaien et al. (2025) analysing big data analytics in Jordanian commercial banks, found that business analytics strategy fully mediated the relationship between big data capabilities and fintech success, a result that is fundamentally identical to the partial mediation model proposed here.

Not all data in the literature support the straightforward positive chain. Queiroz et al. (2025), in a study of IT resource relatedness and organisational agility in European firms, cautioned that governance formalisation could, under certain conditions, reduce the flexibility required for real-time data exploitation, echoing earlier warnings in the governance literature about the risk of bureaucratic rigidity at higher levels of governance maturity. Weritz et al. (2025) similarly found that the relationship between strategic digital capabilities and firm performance was contingent on how those capabilities were deployed, suggesting that governance quality alone does not guarantee performance outcomes in the absence of aligned deployment strategies.

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Al-Alawnh et al. (2025), in a study of BI and financial performance in the banking sector mediated by operational efficiency, found that the governance-performance relationship was stronger in contexts where operational processes were already well structured, suggesting a sequencing dependency analogous to that confirmed in the present study. These qualifications do not invalidate the core concept but alert to the contextual scenarios under which governance maturity is most likely to deliver BI performance gains.

Hypotheses Development

Well-developed data governance frameworks set the rules, stewardship duties, and auditing procedures that businesses use to handle data in an organised manner. Because governance eliminates uncertainty and accountability gaps that lead to low-quality data, data accuracy, completeness, consistency, and timeliness tend to improve when such frameworks are in place (Abraham et al., 2019; Merkus et al., 2023). The first hypothesis is supported by this logic:

H1: Data governance maturity has a positive and significant effect on data quality.

According to Saputra et al. (2023) and Bany Mohammed et al. (2024), employees who routinely work with accurate, complete, and timely data are better positioned to derive important insights from BI systems and tend to assess those systems more positively as decision-support tools. Even technically advanced BI tools lose user trust when data quality is poor. This supports the second theory:

H2: Data quality has a significant positive effect on employees' perception of business intelligence performance.

Data quality is the mechanism by which governance maturity is expected to influence perceptions of BI performance, because governance structures do not directly engage with BI users; rather, they define the data environment those users navigate. A similar transmission pattern was shown by Kankam et al. (2023), in which a quality-related variable transferred the impact of an upstream structural factor to a downstream performance consequence. The third hypothesis is supported by this logic:

H3: Data quality mediates the relationship between data governance maturity and employee perceptions of business intelligence performance.

Synthesis of Literature and Research Gap

Drawing the reviewed material together, three convergences are obvious. Governance maturity is generally related to greater data quality discoveries across sectors and national contexts. Data quality is consistently associated with greater employee perceptions of BI performance, whether examined directly or through mediating variables. And mediated models, where governance shapes quality, which in turn shapes performance, are increasingly the preferred specification in studies that evaluate the complete data management chain rather than its distinct components.

What the literature does not yet provide is an experimentally tested mediated model of the DGM-DQ-EPBI chain, specifically within the Nigerian fintech sector. Nigerian studies in the

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area have examined data governance and digital performance separately (Komolafe et al., 2024), employee perception of BI performance without a governance antecedent (Adewusi et al., 2024), and have addressed the sector through secondary review methods rather than primary empirical testing (Adelusi et al., 2023). No study has simultaneously examined DGM, DQ, and EBI performance as a causal chain in Nigerian fintech using PLS-SEM. The present study overcomes this gap.

Methodology

This study adopted a quantitative cross-sectional survey design. The choice of a quantitative orientation was grounded in the study's primary objective: testing theoretically specified structural relationships amongst latent constructs across a defined organisational population. Such an objective calls for structured measurement, statistical inference, and hypothesis testing as appropriate analytical tools (Shah, 2025; Syengo & Wanyama, 2026). A cross-sectional design was considered suitable, given that the study's central concern is the prevailing state of organisational data governance and data quality arrangements, rather than how those conditions develop or shift over time. Epistemologically, this study aligns with a positivist position, consistent with the mainstream tradition in information systems and management research, which treats social phenomena as measurable and inter-construct relationships as discoverable through rigorous empirical investigation.

The target population comprised professionals employed across data management, information technology, analytics, compliance, and strategy functions in selected fintech firms registered and licensed by the Central Bank of Nigeria (CBN). The CBN's directory of payment service providers and switching companies listed 214 licensed entities as of the first quarter of 2024. Firms were purposively selected from this register based on three institutional criteria: a minimum staff headcount of 100 employees; active operation of at least two customer-facing product lines that process personal data; and a demonstrated willingness to participate, evidenced by formal written access agreements. This institutional sampling logic reflects the study's focus on organisational governance systems rather than individual-level cognition or experience.

A multi-stage sampling procedure was then applied within the selected firms. At the first stage, qualifying firms were identified from the CBN register as described above. At the second stage, respondents within each firm were selected through stratified random sampling, with strata defined by functional department. Stratification was employed to ensure representation across governance, technical infrastructure, analytics, compliance, and senior management roles, each of which is directly relevant to the data governance, data quality, and enterprise business intelligence (EPBI) performance relationship under investigation. The sample size yielded a minimum requirement of 272 respondents for an estimated professional population of 1,500 across the participating firms. This figure also comfortably satisfied the ten-times rule commonly associated with structural equation modelling (Hair et al., 2025), which, given the maximum path count of four in the structural model, would require only 40 observations. Of the 380 questionnaires distributed, 342 were returned in a satisfactory, usable condition, representing a response rate of 90.0 percent and exceeding both sample size benchmarks by a considerable margin. Of the 214 licensed fintech firms on the CBN register, 10 firms met the three institutional criteria and agreed to participate, yielding the analytic sample of 342 respondents. Table 1 presents the distribution of respondents across participating firms.

Data was gathered through a structured, closed-ended questionnaire constructed from validated measurement scales drawn from the data governance, data quality, and EPBI literatures. Section A collected respondent demographic information. Section B measured Data Governance Maturity (DGM) across four sub-dimensions: policy frameworks, stewardship structures, process controls, and metadata management, drawing on the scale developed by Abraham et al. (2019). Section C assessed Data Quality (DQ) using four items spanning correctness, completeness, consistency, and timeliness, sourced from Kankam et al. (2023). Section D measured EPBI performance across four criteria: decision support quality, report correctness, analytical depth, and user satisfaction, derived from Adelusi et al. (2023), Adewusi et al. (2024), Adeyemi et al. (2025) and Adeyemi et al. (2025). All items were scored on a five-point Likert scale anchored at 1 (Strongly Disagree) and 5 (Strongly Agree). Prior to the main data collection, the instrument was pretested with 30 professionals from two non-participating fintech firms, and minor wording adjustments were made in response to the feedback received.

Table 1. Distribution of Respondents Across the Selected FinTech Firms

S/N	Firm	CBN Licence Category	Number of Respondents
1	Firm A	Switching & Processing	38
2	Firm B	Switching & Processing	35
3	Firm C	Switching & Processing	38
4	Firm D	Mobile Money Operator	43
5	Firm E	Mobile Money Operator	38
6	Firm F	Mobile Money Operator	31
7	Firm G	Mobile Money Operator/Switching & Processing	29
8	Firm H	PSSP/Super-Agent	29
9	Firm I	Switching & Processing	31
10	Firm J	Switching & Processing	30
	Total		342

Source: Researchers' Computation, 2026.

Content validity was established through expert panel review. Three academic specialists in information systems and data management, together with two senior fintech practitioners, independently assessed each item for relevance and representativeness. A content validity ratio (CVR) was computed for each item, and items falling below the 0.60 threshold were revised or removed before proceeding with the main data collection (Samad et al., 2023). Construct validity was examined through two forms: convergent validity, assessed by Average Variance Extracted (AVE) values exceeding 0.50 and composite reliability (CR) exceeding 0.70; and discriminant validity, confirmed by Heterotrait-Monotrait (HTMT) ratios below 0.85 for all construct pairs (Hair et al., 2025). Internal consistency was evaluated using both Cronbach's alpha and composite reliability, with a minimum acceptable threshold of 0.70 applied throughout.

Given the cross-sectional nature of the study and the collection of both predictor and criterion variable data from a single respondent source, common method bias (CMB) was considered a potential threat to the validity of the findings. To address this, two complementary procedures were employed. First, Harman's single-factor test was conducted by loading all study items into an exploratory factor analysis and examining the proportion of variance explained by a single unrotated factor. The resulting single factor accounted for 28.3 percent of the total variance, well below the 50 percent threshold, indicating that no single latent factor dominated the data (Jyothi et al., 2026). Second, a full collinearity assessment was conducted at the indicator level by examining the variance inflation factor (VIF) values for all constructs. All VIF values fell below the threshold of 3.3, further supporting the absence of problematic common method variance (Ahmad et al., 2024). Taken together, these diagnostics suggest that CMB did not pose a substantive threat to the integrity of the structural estimates reported in this study.

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The structural hypotheses were tested using Covariance-Based Structural Equation Modelling (CB-SEM), implemented in IBM SPSS AMOS version 23. CB-SEM was selected over its partial least squares counterpart because the study's theoretical model is confirmatory in orientation, the constructs are reflectively specified, and the sample size of 342 is sufficient to meet the distributional assumptions associated with maximum likelihood estimation (Hair et al., 2025). CB-SEM with maximum likelihood estimation is the appropriate technique when the research objective is to assess the degree to which an a priori, theoretically grounded model is consistent with the observed covariance structure of the data (Gaskin et al., 2025). Analysis proceeded in two sequential stages: measurement model assessment, followed by evaluation of the structural model. This two-stage procedure ensures that construct validity is established before structural path estimates are interpreted (Samad et al., 2023).

The structural model positions DGM as the exogenous construct, EPBI performance as the endogenous outcome, and DQ as the mediating variable. Three structural paths are specified: a direct path from DGM to EPBI performance (H1); a path from DGM to DQ and a subsequent path from DQ to EPBI performance, which together constitute the indirect mediated pathway (H2 and H3); and the simultaneous inclusion of both the direct and mediated paths to permit a test of partial versus full mediation. Mediation was tested using bias-corrected bootstrapping with 5,000 resampled subsamples, yielding 95 percent confidence intervals for the indirect effects, consistent with the procedures outlined by Hair et al. (2025). An indirect effect is considered statistically significant when its confidence interval excludes zero.

Ethical clearance for this study was obtained from the relevant institutional review board before data collection. Participation was entirely voluntary, and informed consent was secured from each respondent before questionnaire administration. Respondents were provided with a written information sheet detailing the study's purpose, the voluntary nature of participation, the right to withdraw at any point without consequence, and the assurance of anonymity and confidentiality of all data supplied. No personal identifying information was recorded, and all data were stored securely and used solely for this research. The formal access agreements entered with participating firms pertained only to organisational-level access and did not override or substitute for individual-level informed consent obtained directly from respondents.

Results and Discussion

Demographic Profile of Respondents

Table 2 presents the summary of the demographic characteristics of the 342 respondents. Male respondents constituted 62.6% (n = 214) of the sample, with female respondents accounting for the remaining 37.4% (n = 128). This gender distribution is consistent with the well-documented male concentration in technology-oriented and financial services occupations across sub-Saharan Africa (Adeyemi et al., 2025). In terms of educational attainment, respondents holding master's-level qualifications or an MBA represented the majority at 56.1% (n = 192), followed by those with bachelor's degrees or Higher National Diplomas at 27.2% (n = 93) and doctoral-level respondents at 16.7% (n = 57). This profile reflects the knowledge-intensive nature of fintech work, where employees require strong analytical foundations to engage productively with data governance and business intelligence systems (Komolafe et al., 2024).

Work experience was concentrated in the 6 to 10 years bracket (44.2%, n = 151), with 28.7% (n = 98) reporting 1 to 5 years and 27.2% (n = 93) reporting over a decade of experience. This spread captures perspectives from both operationally established and more recently qualified professionals. Functionally, data and analytics roles accounted for the largest share of respondents (34.8%, n = 119), followed by IT and technology (25.4%, n = 87), compliance and risk (21.1%, n = 72), and management and strategy (18.7%, n = 64). Cross-functional representation of this nature strengthens construct validity, as data governance and BI performance are not confined to any single organisational department (Abraham et al., 2019).

Table 2. Demographic Profile of Respondents

Feature		**Number**	**Percentage**
Gender	Male	214	62.6
	Female	128	37.4
Educational Qualification	HND/B.Sc.	93	27.2
	M.Sc./MBA	192	56.1
	Ph.D.	57	16.7
Experience	1 – 5 Years	98	28.7
	6 – 10 Years	151	44.2
	Over 10 years	93	27.2
Functional Role	Data/Analytics	119	34.8
	IT/Technology	87	25.4
	Compliance/Risk	72	21.1
	Management/Strategy	64	18.7
Total		342	100.0

Source: Field Survey, 2026.

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Descriptive Statistics

Table 3 shows descriptive statistics for all twelve indicators. DGM mean scores ranged from 3.79 (DGM2) to 3.85 (DGM4), indicating moderate to high agreement with governance statements. DQ means ranged from 3.74 (DQ2) to 3.78 (DQ3), reflecting measured satisfaction with data quality. EPBI scores were the lowest, from 3.69 (EPBI3) to 3.75 (EPBI4), suggesting employees view BI system performance positively but not enthusiastically. Standard deviations were narrow (0.88-0.95), indicating response homogeneity. Skewness was small (-0.144 to 0.076) and within +/-1.0, supporting normality (Hair et al., 2019). Kurtosis was uniformly negative (-0.459 to -0.788), suggesting slightly flat distributions. These stats meet the normality assumptions for maximum-likelihood estimation in SEM (Bany Mohammed et al., 2024).

Measurement Model: Convergent Validity and Construct Reliability

Before estimating the structural paths, the psychometric properties of the measurement model were evaluated. Table 4 presents the standardised factor loadings and item-level diagnostics. All analyses were performed within a confirmatory factor analysis (CFA) framework in AMOS, following the procedures recommended by Hair et al. (2019) and consistent with recent SEM-based data governance studies (Merkus et al., 2025; Merkus et al., 2023).

In Table 4, all factor loadings were statistically significant at $p < .001$ and ranged from .805 (EPBI2) to .881 (DGM4), surpassing the minimum threshold of .70 recommended by Hair et al. (2019). Squared multiple correlations (indicator reliability) ranged from .648 (EPBI2) to .776 (DGM4), confirming that each indicator contributed meaningfully to its respective latent construct. Convergent validity was assessed through the Average Variance Extracted (AVE) and Composite Reliability (CR). DGM achieved an AVE of .699 and a CR of .902; DQ produced the strongest psychometric profile with an AVE of .751 and a CR of .926; and EPBI returned an AVE of .679 and a CR of .894, all exceeding the requisite benchmarks. Cronbach's alpha values were .869 (DGM), .901 (DQ), and .847 (EPBI), confirming internal consistency across all constructs. These results are consistent with the measurement standards observed by Bany Mohammed et al. (2024) in their study of BI and analytics usage in the banking sector.

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Table 3. Descriptive Statistics for All Observed Variables (N = 342)

Construct	Variable	Item	N	Min	Max	Mean	SD	Skewness	Kurtosis
DGM	DGM1	Our organisation has clearly defined policies governing data management processes	342	1.00	5.00	3.82	0.91	−0.018	−0.609
	DGM2	There are established standards for data access, ownership, and stewardship in our organisation	342	1.00	5.00	3.79	0.94	−0.144	−0.693
	DGM3	Our organisation regularly audits data governance practices to ensure compliance	342	1.00	5.00	3.81	0.90	−0.089	−0.598
	DGM4	Data governance processes align with regulatory and industry standards in our organisation	342	1.00	5.00	3.85	0.89	−0.032	−0.586
DQ	DQ1	The data available for decision-making in our organisation is accurate and reliable	342	1.00	5.00	3.77	0.95	0.076	−0.732
	DQ2	Data used in our business intelligence systems is complete and free from critical gaps	342	1.00	5.00	3.74	0.93	−0.093	−0.527
	DQ3	Data within our organisation is consistent across different departments and systems	342	1.00	5.00	3.78	0.94	0.018	−0.788
	DQ4	Data produced by our organisation is timely and relevant to the needs of end users	342	1.00	5.00	3.76	0.92	0.069	−0.614
EPBI	EPBI1	Business intelligence tools in our organisation help employees make better-informed decisions	342	1.00	5.00	3.71	0.88	0.064	−0.459
	EPBI2	Employees in our organisation are satisfied with the outputs generated by BI systems	342	1.00	5.00	3.73	0.90	0.024	−0.501
	EPBI3	BI systems improve employee productivity and operational efficiency in our organisation	342	1.00	5.00	3.69	0.91	0.048	−0.631
	EPBI4	Employees perceive BI tools as adding measurable value to strategic and operational activities	342	1.00	5.00	3.75	0.89	0.038	−0.588

Note. DGM = Data Governance Maturity; DQ = Data Quality; EPBI = Employee Perception of Business Intelligence Performance. Skewness and kurtosis values within +/-1.0 indicate approximate normality. Question items adapted from Abraham et al. (2019), Kankam et al. (2023), Saputra et al. (2023), and Bany Mohammed et al. (2024).

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Table 4. *Measurement Model: Standardised Factor Loadings, Reliability, and Validity*

Construct	Construct	Item	Loading (β)	SE	CR	p	R^2	AVE*	CR*
DGM	DGM1	Our organisation has clearly defined policies governing data management processes	.831	.048	19.970	***	.691	.699	.902
	DGM2	There are established standards for data access, ownership, and stewardship in our organisation	.840	.046	20.366	***	.706		
	DGM3	Our organisation regularly audits data governance practices to ensure compliance	.862	.046	21.305	***	.743		
	DGM4	Data governance processes align with regulatory and industry standards in our organisation	.881	—	—	—	.776		
DQ	DQ1	The data available for decision-making in our organisation is accurate and reliable	.864	.047	21.421	***	.747	.751	.926
	DQ2	Data used in our business intelligence systems is complete and free from critical gaps	.873	.045	21.824	***	.762		
	DQ3	Data within our organisation is consistent across different departments and systems	.865	.047	21.435	***	.748		
	DQ4	Data produced by our organisation is timely and relevant to the needs of end users	.871	—	—	—	.759		
EPBI	EPBI1	Business intelligence tools in our organisation help employees make better-informed decisions	.810	—	—	—	.657	.679	.894
	EPBI2	Employees in our organisation are satisfied with the outputs generated by BI systems	.805	.060	16.501	***	.648		
	EPBI3	BI systems improve employee productivity and operational efficiency in our organisation	.830	.062	17.173	***	.688		
	EPBI4	Employees perceive BI tools as adding measurable value to strategic and operational activities	.867	.060	18.130	***	.751		

Note. β = standardised loading; SE = standard error; CR = critical ratio; R^2 = squared multiple correlation (indicator reliability); AVE = Average Variance Extracted; CR = Composite Reliability. Marker indicators (fixed to 1.00) have no SE or CR values. *** p < .001. AVE > .50 and CR > .70 confirm convergent validity and construct reliability for all constructs.*

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Structural Model Fit Assessment

Table 5 presents the global fit statistics for the structural model, estimated using maximum likelihood estimation with 5,000-sample bias-corrected bootstrapping. The model demonstrated an outstanding fit across virtually all reported indices, meeting the established criteria of Hair et al. (2019).

Table 5. Structural Model Fit Indices

Index	Obtained Value	Threshold	Assessment
χ^2/df (CMIN/DF)	1.163	≤ 3.00	Excellent
p-value	.197	> .05	Excellent
CFI	.997	≥ .95	Excellent
TLI	.997	≥ .95	Excellent
NFI	.981	≥ .95	Excellent
IFI	.997	≥ .95	Excellent
RMSEA	.022	≤ .06	Excellent
RMSEA 90% CI	[.000, .042]	Upper < .08	Excellent
PCLOSE	.992	> .05	Excellent
GFI	.971	≥ .90	Excellent
AGFI	.957	≥ .90	Excellent
RMR	.052	≤ .08	Acceptable
HOELTER (.05)	394	> 200	Excellent

Note. Model estimated using Maximum Likelihood estimation with bootstrapping (5,000 samples). Thresholds follow Hair et al. (2019). RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; NFI = Normed Fit Index; IFI = Incremental Fit Index; GFI = Goodness-of-Fit Index; AGFI = Adjusted GFI; RMR = Root Mean Square Residual.

Table 5 presents the structural model fit indices; the chi-square-to-degrees-of-freedom ratio (chi2/df = 1.163) fell well below the ceiling of 3.00, and the associated p-value of .197 exceeded .05, indicating that the model-implied covariance matrix did not differ significantly from the observed data. Incremental fit indices, including CFI (.997), TLI (.997), NFI (.981), and IFI (.997), all met or exceeded the .95 benchmark. The RMSEA of .022, with a 90% confidence interval of [.000, .042] and a PCLOSE of .992, confirms negligible approximation error. The GFI (.971) and AGFI (.957) both surpassed the .90 threshold. The RMR of .052 was within the acceptable range, and the HOELTER index of 394 exceeded 200, confirming adequate sample size for model stability. These indices collectively indicate an excellent-fitting model, warranting confidence in the subsequent path estimates (Adewusi et al., 2024).

Structural Path Coefficients and Mediation Analysis

The structural model is shown in Figure 1. Table 6 reports the structural path coefficients, standard errors, critical ratios, and 95% bias-corrected bootstrap confidence intervals for all hypothesised relationships, including the indirect mediation effect.

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The Effect of Data Governance Maturity on Data Quality

The first hypothesis proposed that data governance maturity would positively predict data quality in Nigerian fintech firms. The path from DGM to DQ produced an unstandardised coefficient of B = .705 (SE = .054), a standardised coefficient of B_std = .694, a critical ratio of 13.143, and a 95% BC CI of [.610, .799] that fully excluded zero ($p < .001$). This result provides strong empirical support for H1. The standardised coefficient of .694 reflects a large practical effect, with DGM explaining 48.2% of the variance in DQ. The finding indicates that formalised data governance structures, encompassing data policies, ownership protocols, compliance audits, and regulatory alignment, constitute the primary antecedent of data quality within the fintech organisations studied. This accords with the argument by Bliznák et al. (2024) that governance frameworks which institutionalise data oversight capabilities directly condition data quality outcomes across organisational units.

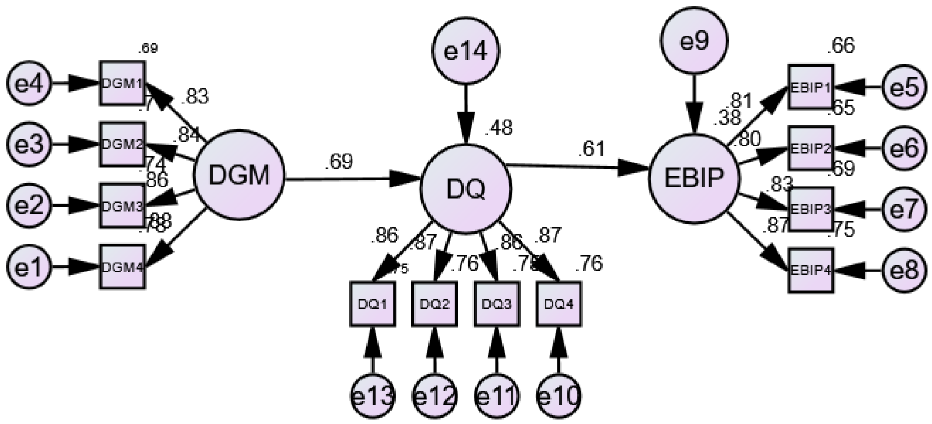

Figure 1. Standardized Structural Model

Table 6. Structural Path Coefficients and Mediation Analysis

Hypotheses	Path	B	Std. Error	B Std.	CR	p-values	95% BC CI	Decision
H1	DGM→DQ	.705	.054	.694	13.143	***	[.610, .799]	Supported
H2	DQ→EPBI	.518	.048	.613	10.734	***	[.434, .607]	Supported
H3	DGM→DQ→EPBI	.365	.038	.426	–	.000	[.293, .444]	Supported

*Note. B = unstandardised coefficient; B (std) = standardised coefficient; SE = standard error; CR = critical ratio; BC CI = Bias-Corrected Bootstrap Confidence Interval (5,000 samples). The indirect effect (DGM -> DQ -> EPBI) represents full mediation; no direct path from DGM to EPBI was specified in the final model. *** p < .001.*

The Effect of Data Quality on Employee Perception of Business Intelligence Performance

The second hypothesis proposed that data quality would positively predict employee perceptions of business intelligence performance. The path from DQ to EPBI yielded B = .518 (SE = .048), B_std = .613, CR = 10.734, and a 95% BC CI of [.434, .607] ($p < .001$), confirming

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H2. The standardised coefficient of .613 reflects a moderately large effect: employees who interact daily with data characterised by accuracy, completeness, consistency, and timeliness are substantially more likely to rate their organisations' BI systems as decision-useful and value-adding. This finding is consistent with Saputra et al. (2023), whose investigation of information quality and job performance in a mandatory system context found that information quality, mediated through perceived usefulness, shapes how users assess system-level contributions to their performance. The present result situates this dynamic within a voluntary BI usage context and extends it to the Nigerian fintech sector.

The Mediating Role of Data Quality

The third hypothesis posited that data quality would mediate the relationship between data governance maturity and employees' perceptions of BI performance. The indirect effect of DGM on EPBI through DQ was estimated at B_indirect = .365 (SE = .038), B_indirect_std = .426, p = .000, with a 95% BC CI of [.293, .444] that strictly excluded zero. These results support H3 and are consistent with full mediation, as no direct path from DGM to EPBI was retained in the final model. The finding indicates that data governance maturity does not directly influence employee BI performance perceptions; rather, its influence is channelled entirely through the quality of the data it produces. This is theoretically coherent: governance structures establish the conditions under which data quality is maintained, and it is through improved data quality that employees come to perceive BI tools as genuinely useful and performance-enhancing (Kankam et al., 2023).

Explained Variance in Endogenous Constructs

Table 7 present the variance for the endogenous constructs. Data governance maturity explained 48.2% of the variance in data quality (95% BC CI: [.398, .566]), a moderate-to-large effect by Cohen's (1988) conventions. Data quality, in turn, explained 37.6% of the variance in employee perception of BI performance (95% BC CI: [.290, .464]), constituting a moderate effect. These variance proportions confirm that the model accounts for meaningful portions of variation in both endogenous constructs and that the theoretical framework is appropriately calibrated to the empirical context. The finding that 62.4% of the variance in EPBI remains unexplained signals the presence of additional determinants, potentially including BI system interface quality, user digital literacy, and organisational change management, that future research should incorporate (Adeyemi et al., 2025).

Table 7. Explained Variance (R^2) for Endogenous Constructs

Endogenous Construct	R^2	Adjusted R^2*	95% BC CI	Interpretation
DQ	.482	–	[.398, .566]	Moderate–Large
EPBI	.376	–	[.290, .464]	Moderate

Note. R2 values represent the proportion of variance in each endogenous construct explained by its predictor(s). Values >= .26 are considered large effects (Cohen, 1988). BC CI = 95% Bias-Corrected Bootstrap Confidence Interval.

Discussion of Findings

This study investigated how data governance maturity influences employees' perceptions of business intelligence performance and whether data quality mediates this relationship within

Nigerian fintech firms. The empirical findings yielded three interconnected conclusions, each of which is examined against evidence from the reviewed literature below.

Data Governance Maturity and Data Quality

The finding that DGM significantly and positively predicts DQ (B_std = .694, $p < .001$) is aligned with a growing body of evidence on the governance-quality nexus. Abraham et al. (2019), established that the exercise of formal authority and control over data management constitutes the primary mechanism through which organisations increase data value and reduce data-related risk. Their framework positions governance structures, specifically those governing data stewardship, policy enforcement, and accountability, as the antecedents of data quality outcomes, which maps directly onto the empirical pattern identified in the present study. Merkus et al. (2023) empirically validated a set of data governance capabilities and demonstrated that organisations with more fully operationalised capabilities exhibited stronger data quality consistency, a conclusion reaffirmed in their subsequent evaluation study (Merkus et al., 2025).

Dahlberg and Nokkala (2015) found that the perceived significance of good data governance was directly tied to the quality and reliability of organisational data. Their conclusion, that governance of data is considered critical to organisations precisely because it conditions data reliability, resonates with the present study's finding that mature governance explains nearly half (48.2%) of the variance in data quality.

Disconfirmatory evidence from Bližnák et al. (2024), noted that whilst governance frameworks are widely associated with improved data quality in theory, empirical studies frequently report implementation gaps, particularly in organisations where governance structures are recently adopted or inadequately resourced. Additionally, Marcucci et al. (2023), found that governance frameworks oriented primarily towards legal compliance rather than operational data stewardship produced weaker data quality outcomes, as compliance-focused governance did not necessarily address the day-to-day data management processes that determine quality.

Data Quality and Employee Perception of Business Intelligence Performance

The significant positive effect of data quality on employee perception of BI performance (B_std = .613, $p < .001$) is consistent with established findings in the information systems success literature. Saputra et al. (2023), found that information quality exerted no significant direct effect on job performance but operated fully through perceived ease of use and perceived usefulness. The present study's full-mediation finding echoes this indirect logic: data quality does not directly alter BI system technical properties, but it shapes how employees perceive those systems as useful and worth engaging with. Bany Mohammed et al. (2024), found that data-related factors, including information accuracy and completeness, were significant predictors of BI system usage levels and satisfaction, reinforcing the quality-perception chain identified here. Hmoud et al. (2023), similarly found that information quality was a significant antecedent of favourable BI system attitudes, with employees who perceived data as reliable and timely reporting stronger intentions to rely on BI outputs for decision-making.

Against this supporting evidence, two studies introduce meaningful qualifications. Saputra et al. (2023) found that in mandatory-use information system contexts, the direct effect of information quality on performance was statistically insignificant, suggesting that where BI system usage is not discretionary, data quality alone may be insufficient to drive performance perception improvements. Whilst Nigerian fintech employees operate in largely voluntary BI usage environments, the presence of compliance and risk roles in the sample introduces a degree of mandatory system engagement that may moderate the quality-perception path.

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Adeyemi et al. (2025) found that system quality, user training effectiveness, and data accessibility collectively moderated how users attributed performance improvements to BI systems, with some users crediting the interface and training experience rather than underlying data quality as the proximate driver of perceived value.

The Mediating Role of Data Quality

The confirmation of full mediation, in which data quality fully transmits the effect of data governance maturity on employees' perception of BI performance (B_indirect_std = .426, 95% BC CI [.293, .444]), is theoretically coherent and empirically meaningful. Kankam et al. (2023), demonstrated that information sharing acted as a mediator between information quality and supply chain performance outcomes, yielding a partial mediation pattern. Whilst the mediation mechanism in their study differs structurally from the present one, their core finding, that quality-related variables do not act directly on performance outcomes but operate through an intermediate transmission mechanism, is conceptually consonant with the full-mediation pattern identified here. Al-Alawnh et al. (2025) similarly found that BI's impact on organisational performance was fully mediated by an intermediate quality-enhancing mechanism, operational efficiency, rather than acting directly on performance. This parallel supports the logic that in data-intensive service organisations, performance impacts travel through an intermediate quality transformation rather than bypassing it.

Aldalaien et al. (2025) found that the direct effect of analytics capability on performance was non-significant, whilst the mediated path through strategy was significant, aligning structurally with the present study's full-mediation finding and reinforcing the notion that, in fintech contexts, governance and analytics capabilities produce their performance effects indirectly.

Contrary evidence is offered by two studies. Pörtner et al. (2025) found that at advanced levels of data maturity, the effect of governance-like structures on organisational data-driven outcomes began to exert a direct influence that was not fully transmitted through intermediate quality variables, suggesting that as firms mature, governance begins to function as an independent performance signal. Ameria (2025) argued that in AI-augmented environments, the governance-quality relationship becomes bidirectional, with data quality feeding back into governance effectiveness, complicating the unidirectional causal chain assumed in the present model and suggesting that future specifications should consider reciprocal relationships.

Conclusion

This study examined the relationship between data governance maturity and employee perception of business intelligence performance in Nigerian fintech firms, proposing data quality as a mediating variable. Drawing on a sample of 342 employees and deploying structural equation modelling with bias-corrected bootstrapping, the study produced three main empirical findings. First, data governance maturity positively and significantly predicts data quality. Second, data quality positively and significantly predicts employee perception of BI performance, accounting for 37.6% of its variance. Third, data quality fully mediates the relationship between data governance maturity and employee perception of BI performance, with the indirect effect (B_indirect_std = .426) supported by a bias-corrected bootstrap confidence interval that excludes zero. These results collectively affirm that the pathway from governance investment to employees' perceptions of BI performance runs entirely through the quality of data produced by governance structures.

This study made contributions to theory, empirical knowledge, and practice in the fields of data governance, data quality, and business intelligence performance. Theoretically, the study extends information quality theory to the fintech ecosystem in sub-Saharan Africa. Empirically, the study is among the first to construct and validate a structural model that explicitly links DGM, DQ, and EPBI in the Nigerian fintech sector. Prior empirical work on BI in Africa has been predominantly conceptual or based on smaller, non-probability samples. In practice, the study adapted and validated scales for DGM, DQ, and EPBI for the Nigerian fintech research context.

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The present findings indicate that governance operates entirely through quality, which has implications for how researchers specify BI success frameworks. The strong effect of data governance maturity on data quality indicates that investments in formalising data governance, through clearly articulated data policies, defined stewardship responsibilities, regulatory alignment, and periodic audits, translate directly into measurable data quality improvements. Fintech firms that invest in BI dashboarding or advanced analytics infrastructure without first establishing mature governance frameworks are likely to encounter a quality ceiling that caps employee-perceived BI performance irrespective of the technological sophistication deployed. For regulatory bodies overseeing Nigerian fintech operations, including the Central Bank of Nigeria and the National Information Technology Development Agency, the study provides evidence that sectoral data governance standards, when genuinely internalised by fintech firms beyond superficial compliance, produce data quality outcomes that enhance employee intelligence at the firm level.

Based on the findings of this study, the following recommendations were made. Fintech organisations in Nigeria should formalise and operationalise data governance frameworks that include documented data policies, assigned data stewards, cross-departmental data standards, and periodic governance audits. BI implementation strategies in fintech organisations should adopt a governance-first sequencing model, in which data quality baseline assessments and governance gap analyses are completed before advanced BI tooling is scaled. Human resource and learning and development functions in fintech firms should invest in data literacy programmes that enable employees across non-technical roles, particularly in compliance/risk and management/strategy, to critically evaluate data quality and interpret BI outputs within the context of governance limitations. The Central Bank of Nigeria and allied regulators should consider extending existing data governance guidance to specify minimum data quality management standards, recognising that governance compliance alone does not guarantee the quality outcomes that drive employee-level BI performance.

Future research should employ longitudinal panel designs to test causal directionality in the DGM-DQ-EPBI relationships identified here, given that cross-sectional designs cannot establish causality. Multi-country studies spanning other African fintech markets, including Ghana, Kenya, and South Africa, would test the generalisability of these findings and contribute to a cumulative evidence base for governance-driven BI performance in emerging economies.

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