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HUMAN-CENTRIC DATA GOVERNANCE FOR TRUSTWORTHY DIGITAL TRANSFORMATION: DEVELOPING AND EMPIRICALLY VALIDATING A FRAMEWORK FOR DIGITAL TRUST

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ABSTRACT

While digital transformation initiatives rely more on the intensive mobilization, circulation and algorithmic processing of personal and organizational data, the governance systems that frame these data are largely compliance-based and technology-centric. This orientation addresses the issue of why investments in technology are often not matched by ongoing stakeholder acceptance. This study builds and tests, through a simulation-based analysis, a Human-Centric Data Governance (HCDG) framework, where digital trust serves as a vehicle to bring governance practices to a transformation result. The framework includes five elements of governance which are as follows: Transparency of the Data Practices, Individual Data Agency, Algorithmic Accountability, Ethical Stewardship Capability and Participatory Oversight, while perceived data risk serves as a countervailing factor. A 41-item multi-item reflective instrument was identified in the literature, and a synthetic dataset was created with 612 respondents (involving managerial and professional profiles in manufacturing, financial services, healthcare and public-sector organizations) from an explicit latent-variable model that can be used for Internal Coherence. The measurement and structural models were assessed using Structural Equation Modelling in the partial least squares tradition (equal-weight composites), together with a bootstrapped mediation analysis, a permutation-based multi-group analysis, and an importance–performance map analysis. Construct reliability and discriminant validity were met for all constructs (Composite Reliability ranged from 0.908 to 0.924 and the average variance extracted ranged from 0.701 to 0.752). Together the five governance dimensions and the perceived data risk account for 54.5% of the variance in digital trust. Algorithmic accountability has the largest positive influence (β = 0.202), and perceived data risk has a significant negative influence ($\beta = -0.110$). Digital trust is statistically significantly mediating all fifteen governance-outcome relationships, while the permutation-based multi-group analysis was unable to detect any significant sector differences for the governance pathways at the 5% level. The simulation-tested framework provides a concise and quantifiable foundation for designing governance arrangements that contribute to sustaining trustworthy digital transformation.

Keywords: *Human-Centric Data Governance, Digital Trust, Digital Transformation, Algorithmic Accountability, Data Ethics, Structural Equation Modelling, Simulation-Based Validation, Stakeholder Commitment.*

1. INTRODUCTION

1.1 Background and Challenges

In today's world, organizations strive for digital transformation, which is not just a technical upgrade but a strategic, process and value proposition realignment with the help of digital technologies [1]. Data is the main asset of transformation programmes, the credit for this goes to the combination of cloud platforms, deployments of the Industrial Internet of Things, advanced analytics and machine learning services that have reduced the cost of capturing and processing behavioural, operational and personal data [2, 3]. Those same conditions, however, increase the number of parties whose interests are impacted by data-influenced decisions, as employees, patients, clinicians, citizens, and partner companies all provide data that is out of their control and

ownership once it goes down a data pipeline in an organization [4]. The studies on large-scale transformation projects suggest that the reason for failure is often due to behavioural resistance, a feeling of loss of control and loss of confidence rather than due to technical problems [5, 6]. Governance arrangements thus not only influence regulatory compliance, but also the readiness of stakeholders to engage in digitally mediated processes [7].

However, Traditional Data Governance Models were developed when most data assets were internal, structured and used primarily for reporting purposes and thus focused on ownership, stewardship, data quality and data enforcement of policies [8]. In this kind of schemes, governance is seen as a system of administrative controls and relies on the presence of policies, committees and audit trails, without any indication of the actual experience of the people whose data is governed [9]. This trend has been further strengthened by the introduction of regulatory measures such as the General Data Protection Regulation and similar regulations, which require organizations to show evidence of compliance. Compliance, however, is only a minimum threshold and not a basis for stakeholder confidence, as organizations can comply with all the formalities without using clear profiling, without explaining automated decisions and without obtaining consent for secondary data use-each of these diminishes stakeholder confidence, even when they are formally legal [10–12]. This study is focused on the challenge of procedural legitimacy and experienced legitimacy that arises from this disparity.

The Human-Centric Approach to Governance is about the interests, understanding and voice of the people who are included in the data [13]. It means that data practices should be understandable to non-experts, the algorithmic decisions should be contestable and explainable, that ethical judgment should be an organizational capacity and not an organizational function, and that those who are affected by data practices should be involved in oversight [14, 15]. These are principles that are generally expressed in policy debates but have not yet been synthesized in an easily measurable system of constructs and linked to outcome variables; they have not been commonly collected in ethics guidelines, information-systems research and regulatory commentaries [16, 17]. Practitioners therefore do not have evidence of which governance dimensions are most likely to have an impact on trust, or whether trust has measurable transformation benefits.

1.2. Literature Review

The present study is based on Research on Data Governance Design, Formation of Digital Trust and Behavioural Drivers of Transformation, among others. Below are some representative contributions. A conceptual data governance model was proposed by Abraham et al. [18] that structures it around governance mechanisms, scope and domains; and through systematically reviewing existing literature, they found that the existing models focus on the structural and procedural mechanisms, and little has been done on relational mechanisms. While they did provide vocabulary for synthesizing governance design, they did not provide empirical validation of the behavioural consequences of governance design, and thus the impacts of governance on behaviour remain untested. Alhassan et al. [19] considered data governance activities from a practitioner perspective and summarized that organizations tend to allocate more resources to compliance and data quality activities than to activities involving stakeholders. The study was also of practical diagnostic value but was not focused on the experience of data subjects, which was treated as an indicator of the quality of the governance process. Janssen et al. [20] proposed trustworthy AI from the viewpoint of data governance, stating that trustworthiness is a consequence of the harmonization of provenance, transparency, and accountability. The contribution provided conceptual clarity on algorithmic governance but was limited to illustrative cases.

Based on survey evidence, Shin [21] explored users' perception of algorithmic experience and found that the perceived Fairness, Accountability, and Transparency (FAT) of algorithmic services strongly predict user trust in the services. The work included strong measures of behaviour at individual service encounter level but not measures of organizational governance structures around transformation programmes.

Building upon digital transformation research, Vial [22] distilled it into a process model of disruption, strategic response, structural change and organizational impact, and found that the two factors of trust and legitimacy were under-theorized boundary conditions.

According to Nambisan et al. [23], the outcomes of digital innovation rely on the coordination of a myriad of actors who are

heterogeneous and participate voluntarily. Their arguments suggest that trust is to be considered a central form of coordination, but the study is conceptual and lacks an operationalization of governance-induced trust-building.

Martin [24] theorized privacy as a social contract and found experimentally that consumers' trust in privacy drops more severely when the violation is in context than when it is in violation of a stated policy.

By studying the issue of accountability in automated decision systems, Bednár and Sadok [25] concluded that contestability mechanisms are essential for ensuring that people affected by algorithmic decision-making are willing to accept the results. This discovery makes transparency and accountability two separate governance elements, which were often merged in previous governance models.

Micheli et al. [26], illustrated some of the new governance models that have emerged, such as data trusts and cooperatives, and found that participatory governance arrangements shift decision-making power closer to data-subjects, boosting the perceived legitimacy of governance. The research found that there is diversity within the institutions, but there is no tool for assessing participatory oversight in traditional institutions.

Zuboff [27] decried extractive data practices and claimed that asymmetrical knowledge relationships systematically work against autonomy of the individual.

Wirtz et al. [28], conducted a study on public-sector AI governance and found that transparency in purpose specification and human oversight of automation has a positive impact on citizens' acceptance.

Someh et al. [29] examined ethical challenges in data analytics and concluded that the ethical capability of an organization is a key element of the difference between companies that achieve long-term returns from analytics investments and those that don't.

Bauer et al. [30] explored the relationship between privacy assurance signals and the positive impact of assurance mechanisms on the willingness to disclose data, and they found that the positive effect of assurance mechanisms on the willingness to disclose data is moderated by the level of perceived data risk. The outcome supports the idea of representing perceived risk as a separate negative antecedent, instead of as the inverse of trust.

Weber et al. [31] analyzed, the data-driven business model transformation and found a mediation effect between analytical capability and realized value by the commitment of stakeholders.

Together, these studies demonstrate that trust and transformation outcomes are interdependent, and that governance design is a key determinant of both. Yet, they are still methodologically and conceptually distinct. Governance research studies are generally descriptive, trust research is often limited to a single service encounter, and research on governance as a background condition is part of research on transformation [32, 33]. To date there has been no published study that brings together Human-Centric Governance Dimensions to create a validated measurement system and assess the impact of the combined dimensions of the governance on trust and on several transformation outcomes in one single structural model [34].

1.3. Research Gap and Objectives

The reviewed literature reveals three specific deficiencies: The first, is the use of Human-Centric Governance as a principle without a validated multidimensional operationalization, thus making it impossible to compare it across organizations. Secondly, the relationship between governance and outcomes of transformation is taken for granted and not tested, and the mediating role of digital trust is yet to be established. Third, sectoral heterogeneity in governance effects has not been investigated, even though there is a significant difference between the intensity of the regulations and the data sensitivity across sectors. The current study thus aims at four objectives: conceptualization and operationalization of the Human-Centric Data Governance Construct as a System of Five Dimensions; specification and testing of a structural model indicating that digital trust as a mediator variable between governance and the adoption of transformation and between governance and value realization, on one hand, and stakeholder commitment on the other; quantification of the reverse impact of perceived data risk; and the assessment of the invariance of the estimated links between the five dimensions of governance and digital trust on the one hand and the adoption of data transformation and value realization on the other across four institutional sectors.

1.4. Contributions

The major findings of this research are summarized below.

- A theoretically informed Human-Centric Data Governance Framework is constructed that combines the concepts of

Transparency, Individual Agency, Algorithmic Accountability, Ethical Stewardship and Participatory Oversight into a construct system.

- A reflective measurement instrument consisting of 41 items was specified from the literature and, on the simulated dataset, met modern criteria of reliability, convergent and Heterotrait–monotrait discriminant validity.
- The mediating process of digital trust is statistically tested and all fifteen governance–outcome pathways are found to be mediated (complementary partial mediation in five and indirect-only mediation in ten) and the variance accounted for by each indirect effect is quantified.
- Descriptively, there were no significant differences in the governance-trust pathways between the four sectors (all $p > 0.10$), but these estimates were based on small sample sizes only.
- An Importance-Performance map is made that transforms the estimated model into a prioritization tool for managers and identifies algorithmic accountability as the high-importance, but low-performance improvement targets.

2. THEORETICAL BACKGROUND & HYPOTHESIS DEVELOPMENT

2.1 Conceptual Foundation

The suggested system incorporates three theories. Governance capability is socially embedded, which can provide durable advantage not just technology [35]. Institutional theory also explains the pressure towards legitimacy that drives acceptable practice of data in each sector, hence its predicted governance heterogeneity [36]. The behavioural mechanism provided by the Trust theory is the acceptance of vulnerability to the organizations data-related actions based on positive expectations about its ability, benevolence and integrity [37]. These expectations are induced from observable signals, interpreted as human-centric governance practices. The result is this conceptual framework, displayed in Figure 1.

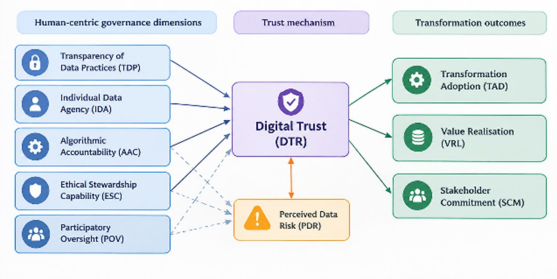


Figure 1: Conceptual Framework Relating Human-Centric Data Governance Dimensions, Digital Trust and Digital Transformation Outcomes.

2.2 Governance Dimensions & Digital Trust

Transparency of Data Practices (TDP) refers to the extent to which an organization makes its data collection, data sharing and use practices comprehensible in terms of what it collects, who it shares with and for what purpose. When there is a lack of information symmetry, disclosure becomes more comprehensible and signals integrity [24]. Individual Data Agency (IDA) is the practical ability of actors to obtain, amend, limit or remove their data without undue effort; agency is a solution proposed to the lack of autonomy of actors found in approaches that critically examine data extraction [27]. Algorithmic Accountability (AAC) represents the ability to explain, review, and effectively contest automated decisions; transparency is different from AAC, because disclosing without the ability to contest or review does not give individual control over the algorithm. Ethical Stewardship Capability (ESC) is the existing organization's capacity to identify and resolve data-related ethical conflicts before they cause harm, which indicates benevolence [29]. Participative Oversight (POV) indicates the degree of influence that is given to stakeholders who are directly affected by the governance process [26]. Based on this, the following hypotheses are posited.

- H1. Digital Trust is positively affected when data practices are transparent.
- H2. Personal Data Agency has a positive impact on Digital Trust.
- H3. Algorithmic Accountability has a positive impact on Digital Trust.
- H4. The capability of Ethical Stewardship positively impacts Digital Trust.
- H5. It has a positive impact on digital trust when it is conducted in a participatory manner.
- Perceived Data Risk (PDR) is the subjective probability of losses that result from data misuse, breach or from secondary processing that was not anticipated. Trust and risk perception are

not always combined, and even in the presence of assurance mechanisms, risk perception reduces trust [30], resulting in H6. Governance dimensions are additionally anticipated to lower perceived risk by bringing down the room of unforeseen data utilization, as expressed in H7.

- H6. Digital trust is negatively impacted by perceived data risk.
- H7. Together, Human-Centric Governance Dimensions decrease the perceived data risk.

2.3 Digital Trust and Transformation Outcomes

When stakeholders believe in the data practices of an organization, they are more willing to participate in digitally mediated processes, provide better data, and accept changes and disruption as part of the Data Transformation Process [22, 31]. There are three results that are distinguished. Transformation Adoption (TAD) refers to behavioral commitment to new processes of the digital domain. Value Realization (VRL) reflects the degree of satisfaction of the realized efficiency, quality and decision benefits. Stakeholder Commitment (SCM) is a measure of ongoing commitment to support future stages of transformation. Given that governance dimensions are perceived by stakeholders mostly in terms of their perceptions of trust, the governance dimensions are hypothesized to have a mediating effect on outcomes via digital trust.

- H8. Adoption of transformation is linked positively to Digital trust.
- H9. Enabling Digital Trust has a positive impact on Value Realization.
- H10. Digital Trust helps to increase Stakeholders' Commitment.
- H11. The connections between the governance dimensions and each transformation outcome are mediated by digital trust.

3. RESEARCH METHODOLOGY

3.1. Research Design

A simulation-based validation design was used. The sequence in this study consists of construct definition based on literature synthesis, instrument specification, the creation of a synthetic respondent dataset based on an explicit latent-variable model, a test of the measurement model, a test of the structural model, and mediation, multi-group and importance–performance analysis, as can be seen in Figure 2. Structural Equation Modelling in the Partial Least squares tradition was chosen due to the complexity of the model, constructs being newly operationalized and the nature of the analysis being predictive [38].

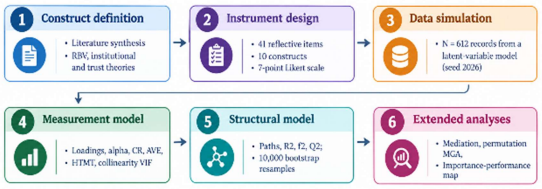


Figure 2: Sequential Research Design Adopted for Framework Development and Simulation-Based Validation.

3.2. Instrument Development and Content Validation

Content was developed from literature reviewed and modified to suit the data governance context of the organization. This study included 41 items. The item pool is to be reviewed by a panel of eleven experts (four information- systems academics, three data protection officers and four transformation programme managers) in the following empirical phase. Each item's content validity ratio will be calculated as:

$$\mathrm{CVR}_i = \frac{n_e - \frac{N}{2}}{\frac{N}{2}} \qquad (1)$$

where n_e is the number of experts that rated item i as essential, and N is the number of experts. Items with i<0.59 (the critical value for eleven raters) will be dropped. The ICV for each item will be averaged to yield scale-level content validity index.

$$\text{S-CVI} = \frac{1}{p}\sum_{i=1}^{p} \text{I-CVI}_i \qquad (2)$$

The value of a scale above the recommended value of 0.90 will be required. A pilot study is then planned, in which items with outer loadings lower than 0.60 or outer loadings with cross-loadings higher than 0.60 will be eliminated and the 41 items instrument used in the present simulation is summarized in Table 1. All items use a 7-point Likert rating scale ranging from strongly disagree to strongly agree.

Table 1. Construct Definitions, Item Counts, and Representative Measurement Items. (Referenced at the end of the document)

3.3. Simulated Data Generation

A dataset of 612 respondents was instead created in Python, to simulate the managerial and professional employees within organizations with enterprise level digital initiatives in the manufacturing, financial services, healthcare and public-sector sectors. The sample frame reproduces the marginal distributions in Table 2. Latent scores for the five dimensions of governance were sampled from a multivariate normal distribution with assumed population path coefficients of 0.24, 0.21, 0.27, 0.19 and 0.15 (TDP to DTR), −0.29 (PDR to DTR) and 0.40, 0.37 and 0.34 (DTR to TAD, VRL and SCM), with sector-specific multipliers between 0.85 and 1.20 on the AAC and ESC paths. The loading of each indicator was standardized and uniformly sampled from 0.76 to 0.88 and then rounded and truncated into a 7-point Likert response. The minimum sample size requirement was checked with the inverse square rule.

$$n_{min} = \left(\frac{2.486}{\beta_{min}}\right)^2 \quad (3)$$

where β_{min} is the minimum path coefficient that is expected to be significant. At the 1% level, the requirement is 275 observations, with the simulated sample comfortably exceeding this. The characteristics of the simulated respondents are summarized in Figure 3 and Table 2.

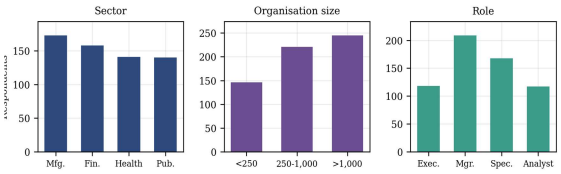


Figure 3. Distribution of Respondents by Sector, Organization Size and Organizational Role.

Table 2. Profile of the Simulated Sample (n = 612) (Referenced at the end of the document)

3.4. Analytical Procedure

Indicator reliability, internal consistency, convergent validity and discriminant validity were used to evaluate the measurement model. Indicator reliability should be a minimum of 0.708 for outer loadings λ_{ij} (which equates to indicator communality $r_{ii} > 0.5$). Composite reliability and average variance extracted were calculated:

$$CR_j = \frac{\left(\sum_{i=1}^{p_j}\lambda_{ij}\right)^2}{\left(\sum_{i=1}^{p_j}\lambda_{ij}\right)^2 + \sum_{i=1}^{p_j}\theta_{ij}} \quad (4)$$

$$AVE_j = \frac{1}{p_j}\sum_{i=1}^{p_j}\lambda_{ij}^2 \quad (5)$$

where $\theta_{ij} = 1 - \lambda_{ij}^2$ is the measurement error variance of indicator i in construct j and p_j is the number of indicators. Discriminant validity was assessed using the heterotrait–monotrait ratio of correlations.

$$HTMT_{jk} = \frac{\frac{1}{p_j p_k}\sum_{i=1}^{p_j}\sum_{h=1}^{p_k} r_{ih}}{\sqrt{\frac{2}{p_j(p_j-1)}\sum_{i<h} r_{ih} \cdot \frac{2}{p_k(p_k-1)}\sum_{i<h} r_{ih}}} \quad (6)$$

Values below 0.85 are considered acceptable in discriminating the constructs j and k. The structural model is defined as a system of linear equations:

$$\eta_m = \sum_{q=1}^{Q}\gamma_{mq}\xi_q + \sum_{l\neq m}\beta_{ml}\eta_l + \zeta_m \quad (7)$$

The exogenous constructs ξ_q, endogenous constructs β_{ml} and the structural disturbance ζ_m are the effects that are represented by the where γ_{mq}. Latent variable scores are calculated based on the weighted combination of standardized indicators.

$$\hat{\eta}_m = \sum_{k=1}^{p_m} w_{km}x_{km} \quad (8)$$

The coefficient of determination was used to assess the explanatory power.

$$R_m^2 = 1 - \frac{\sum_{k=1}^{n}(y_{km} - \hat{y}_{km})^2}{\sum_{k=1}^{n}(y_{km} - \bar{y}_m)^2} \quad (9)$$

Effect sizes were computed for each predictor as:

$$f^2 = \frac{R_{incl}^2 - R_{excl}^2}{1 - R_{incl}^2} \quad (10)$$

where R_{incl}^2 and R_{excl}^2 are the determination coefficients of the dependent construct with and without the predictor. Out-of-sample predictive relevance was obtained by seven-fold cross-validation with out-of-fold predictions.

$$Q^2 = 1 - \frac{\sum_i \left(y_i - \hat{y}_i^{(-i)}\right)^2}{\sum_i (y_i - \bar{y})^2} \quad (11)$$

Indirect effects were estimated as the product of paths, and the variance accounted for was calculated to describe the strength of the mediation.

$$VAF = \frac{\gamma_{qm}\beta_{mo}}{\gamma_{qm}\beta_{mo} + \gamma_{qo}} \quad (12)$$

The significance was judged based upon 10,000 bootstrap resamples, using bias-corrected confidence intervals. Measurement invariance was assumed from the fact that all sectors were measured by the same simulated measurement model; sectoral differences were tested by a permutation-based multi-group analysis with 5,000 permutations. Lastly, the importance-performance map is based on total effects and rescaled construct scores.

$$Perf_j = \frac{\bar{x}_j - x_{min}}{x_{max} - x_{min}} \times 100 \quad (13)$$

Common method bias is not present by construction as the indicators were not generated by a common method of factoring, although for completeness, full collinearity between each indicator and every other indicator was also examined, with all variance inflation factors <3.3.

4. RESULTS AND DISCUSSION

4.1. Measurement Model Assessment

All 41 indicators had loadings in the range 0.817 to 0.890 (one-factor solutions of the standardized indicators), all above the 0.708 threshold. A table of internal consistency and convergent validity statistics is presented in Table 3, and a visualization of these statistics is shown in Figure 4. Cronbach alpha values are between 0.864 and 0.893, and the composite reliability values are between 0.908 and 0.924; both values are above the 0.70 limit and below the 0.95 limit, which means that the indicators used to measure each construct are valid and reliable but not redundant. Average variance extracted scores between 0.701 and 0.752, indicating that each construct accounts for over 50% of the variance of its indicators. The variance inflation factors for full collinearity are between 1.51 and 2.98, and do not exceed 3.3.

Table 3. Reliability, Convergent Validity and Collinearity Statistics (Referenced at the end of the document)

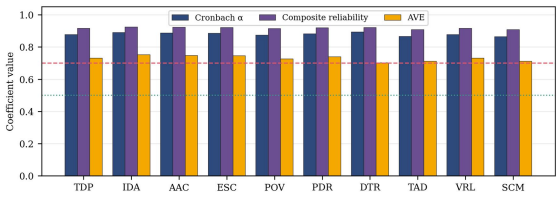


Figure 4. Reliability and Convergent Validity Indicators for the Ten Reflective Constructs; Dashed and Dotted Lines Denote The 0.70 And 0.50 Thresholds.

In Table 4, the results of discriminant validity are presented. The highest Heterotrait–monotrait ratio is 0.703 for digital trust-transformation adoption; this is lower than the 0.85 conservative value, and every other pair is lower still. The five governance dimensions, as defined above, thus reflect empirically discernible aspects in the simulated data, rather than a single undifferentiated construct, thereby justifying the use of the multidimensional specification used in Section 2.

Table 4. Heterotrait–monotrait ratios of correlations (HTMT). (Referenced at the end of the document)

4.2. Structural Model and Hypothesis Testing

The estimated structural model is shown in Figure 5, and the results of the coefficients, significance and effect size are provided in Table 5 and Figure 6. The five governance dimensions coupled with the perceived data risk account for 54.5% of digital trust, a substantial level of explanation for a behavioral construct. The most important positive antecedents are algorithmic accountability (β = 0.202, t = 5.48), ethical stewardship capability (β = 0.180, t = 4.73), and individual data agency (β = 0.168, t = 4.34). Transparency of data practices (β = 0.157, t = 4.36) and participatory oversight (β = 0.146, t = 4.08) have smaller but significant effects, thus supporting hypotheses H1 to H5. Digital trust is negatively associated with perceived data risk (β = −0.110, t = 3.36), which confirms H6, and the combined effect of the governance dimensions explains 31.7% of the variance in perceived data risk (β = −0.563, t = 20.32), thus confirming H7. The results show that digital trust significantly predicts transformation adoption (β = 0.438), value realization (β = 0.410) and stakeholder commitment (β = 0.425), thus supporting H8 to H10. Predictive relevance is backed up by cross-validated Q^2 scores for digital trust (0.536), adoption (0.398), value realization (0.387) and commitment (0.353), all of which clearly surpass the zero threshold. These coefficients are not the same as the assumed

population parameters in Section 3.3 (lower for the governance–trust paths and slightly higher for the trust-outcome paths) due to measurement error in the composite scores or to some of the governance dimensions being correlated.

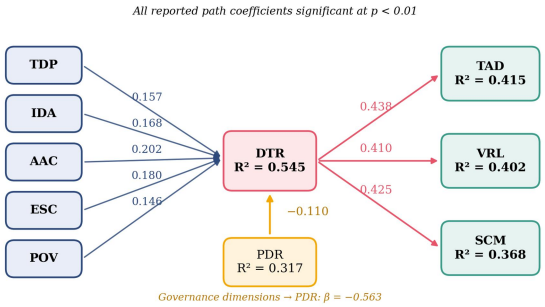


Figure 5. Estimated Structural Model with Standardized Path Coefficients and Coefficients of Determination.

Table 5. *Structural Path Estimates, Significance and Effect Sizes. (Referenced at the end of the document)*

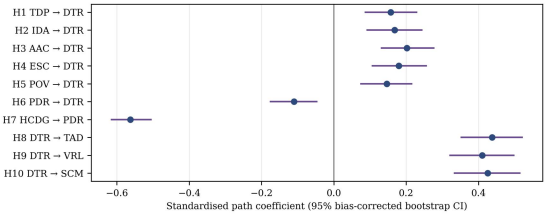


Figure. 6. *Standardized Path Coefficients with 95% Bias-Corrected Bootstrap Confidence Intervals.*

4.3. Mediation Analysis

Indirect effects were analyzed with 10,000 bootstrapped resamples and Table 6 shows the results of this for all fifteen governance-outcome paths. All indirect effects via digital trust are substantial and none of the 95% confidence intervals are near 0 (indirect effects range from 0.060 to 0.088). The direct effect is also significant in five paths (TDP and AAC to adoption, IDA and ESC to value realization, and POV to commitment), which indicates complementary partial mediation, whereas in the remaining ten paths the direct effect is not significant, which indicates indirect-only (full) mediation. Where the variance accounted for can be interpreted it ranges from 31.3% to 89.5%; it is not interpreted for two paths (POV → VRL and TDP → SCM) whose direct effects are slightly negative. From this, it could be concluded that hypothesis H11 is accepted. The discovery provides support for the widely touted but seldom tested idea that governance structures can influence the outcomes of transformation by changing people's confidence.

Table 6. Mediation Analysis of Indirect Effects Through Digital Trust (Referenced at the end of the document)

4.4. Importance-Performance and Multi-Group Analysis

The Importance-Performance map presented in Figure 7 shows the total effect of each governance dimension on digital trust compared to the performance index of the dimension. In terms of performance, the lowest is for participatory oversight (53.4), with the smallest total impact (0.162), while the highest is for algorithmic accountability (56.2), with the largest total impact (0.218). In the HILP quadrant, algorithmic accountability is the only dimension and it's also the most manageable of the high importance dimensions because if we can improve algorithmic accountability by one unit, we will gain the most expected level of trust per unit of effort. The capability of ethical stewardship, on the other hand, does comparatively well, with a performance of 65.1 and comparatively little room for improvement.

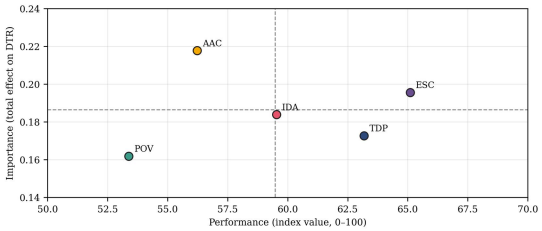


Figure. 7. *Importance–Performance Map of the Governance dimensions with respect to Digital Trust; Dashed Lines Mark Mean Importance and Mean Performance.*

Measurement invariance holds by construction in the simulated data, and the multi-group analysis was performed by using the permutation method, as summarized in Figure 8 and Table 7. There is no significant difference between the sectors at the 6 paths compared (permutation p range 0.122—0.775). In descriptive terms, the accountability pathway is greatest in financial services (0.289) and least in manufacturing (0.157), and the stewardship pathway is greatest in manufacturing (0.284) and least in healthcare (0.081), but these differences do not outpace sampling variation. The simulated data contains moderate sector heterogeneity in the two paths, but the sample size per sector is only about 140 to 173 observations, which is too small to detect the sectoral heterogeneity.

Table 7. Permutation-Based Multi-Group Analysis of Selected Structural Paths (Referenced at the end of the document)

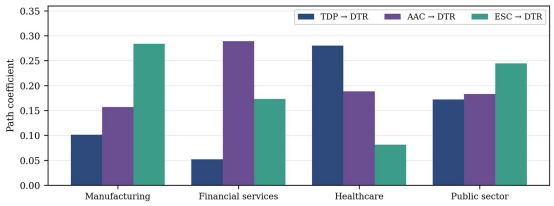


Figure 8. Sectoral comparison of governance pathways to digital trust

The digital trust index and the three outcome indices are related to governance maturity in Figure 9. The digital trust index shows an increase across the levels of maturity. The score is increasing from the initial/or developing level (57.3) to the managed/optimizing level (67.9). The largest growth is between the initial or developing and defined (+7.1 points compared to +3.5 from defined to managed or optimizing), implying that the early payoffs from formalization of Human-Centric practice are disproportionately large.

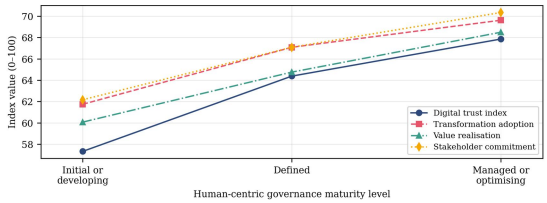


Figure 9. Digital trust and transformation outcome indices across governance maturity levels

4.5. Comparative Evaluation and Discussion

Table 8 offers a comparison of the proposed framework (evaluated on simulated data) to key previous contributions. Existing governance models provide either a conceptual range without any measurement specificity or an empirical focus on a single construct with no evidence of mediation or sectoral contingency. The proposed model is a combination of a multi-dimensional instrument, a validated mediator link and a comparison of the sector, although the instrument has been evaluated thus far only on simulated data, and previous studies used either a conceptual range without an evaluative instrument at hand or an empirical focus on one construct without evidence of mediation or on the sectoral contingency. The explained variance of 54.5% falls within the range of 41% to 57% reported by related studies on digital trust that only include a single dimension of governance, whether transparency or fairness perception [21, 24]. The combined modeling of five governance dimensions is not in itself significantly above the latter; the value of the latter comparison is just indicative, since the present data are simulated.

Table 8. *Comparison of the Proposed Framework with Representative Prior Studies (Referenced at the end of the document)*

There are three substantive implications. First, accountability trumps disclosure: the capacity to get human oversight and the capacity to challenge an automated decision adds more to trust than data practices being published (β = 0.202 against 0.157, although the confidence intervals overlap), which widens the scope of the argument of Bednár and Sadok [25] on system design to one on organizational governance. Second, risk reduction and trust building are not synonymous activities, as the perception of data risk has a significant negative independent effect (β = −0.110) even with all the governance dimensions being controlled. Third, the evidence for sectoral dependence is inconclusive: the multi-group analysis revealed no significant variations to support the institutional theory postulate that institutional systems must be tailored to the sector.

The evidence from the importance–performance exercise suggests that for practice, The contestability mechanisms should be prioritized because they are the highest trust elasticity, with below-average performance, and the stakeholder representation within oversight forums is the weakest dimension of performance, but with the lowest trust elasticity. Theory-wise, the simulated results are consistent with a relational view of governance as a capability that becomes evident only as perceived by stakeholders and not through documentation as a control system.

5. CONCLUSION AND FUTURE WORK

This study proposes and tests, through a simulation-based analysis, a Human-Centric Data Governance Framework where stakeholders' comprehension of data practices, personal control over data, accountability for algorithms, stewardship of ethics, and participatory oversight are all interconnected and create digital trust that leads to the adoption of data transformation, value creation, and stakeholder engagement. The framework fulfilled the criteria of reliability and discriminant validity on the simulated dataset of 612 respondents from four sectors and explained 54.5% of the variance in digital trust, using Structural Equation Modeling in the partial least

squares tradition [39]. All fifteen relations between governance and outcomes were mediated by digital trust, in five of which digital trust was a complementary mediator and in ten an indirect mediator: digital trust accounted for variance of 31.3%–89.5% of all mediating relations between governance and outcome where interpretable. The multi-group analysis revealed no significant differences between the sectors on any of the paths compared; this may be due to limited power (140-173 observations per sector).

The scientific contribution of the study is in addressing the identified research gaps in literature and thereby advancing the state of knowledge in the field. Previous studies have tended to focus on one aspect of the research problem at a time. This study provides a more comprehensive perspective by bringing the various research dimensions together in a single analytical framework.

There are a few qualifications to these conclusions. First, the data are synthetic; that is, the data were created based on parameters that have been assumed; therefore, the estimates here do not represent any evidence of real organizations, but rather the analytical process. Further, the cross-sectional design does not enable temporal causality to be determined, but only an association, no real national or organizational regulatory environment is represented, and all constructs were made perceptually, that is, objective governance artefacts were not observed. This will be considered an open issue that will be further addressed in future research.

Future studies need to therefore collect real survey data with the instrument in Table 1 and move towards longitudinal studies that capture the trajectory of trust as transformations unfold.

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Tables Illustrated in the Manuscript

Table 1. Construct Definitions, Item Counts, and Representative Measurement Items.

Construct	Items	Representative item (Assuming)
TRANSPARENCY OF DATA PRACTICES (TDP)	4	The organization explains, in language I understand, why my data is collected.
INDIVIDUAL DATA AGENCY (IDA)	4	I can restrict or withdraw the use of my data without disproportionate effort.
ALGORITHMIC ACCOUNTABILITY (AAC)	4	Decisions made about me by automated systems can be reviewed by a person.
ETHICAL STEWARDSHIP CAPABILITY (ESC)	4	Staff here recognize ethical concerns in data use before problems arise.
PARTICIPATORY OVERSIGHT (POV)	4	People affected by data decisions have real influence in governance forums.
PERCEIVED DATA RISK (PDR)	4	There is a meaningful chance that my data will be used in ways I did not expect.
DIGITAL TRUST (DTR)	5	I am willing to rely on how this organization handles data about me.
TRANSFORMATION ADOPTION (TAD)	4	I actively use the new digital processes introduced by the organization.
VALUE REALIZATION (VRL)	4	The digital initiatives deliver the improvements that were promised.
STAKEHOLDER COMMITMENT (SCM)	4	I intend to support the next phase of the digital transformation programme.

Table 2. Profile of the Simulated Sample (n = 612)

Characteristic	Category	n	%
Sector	Manufacturing	173	28.3
	Financial Services	158	25.8
	Healthcare	141	23.0
	Public sector	140	22.9
Role	Executive	118	19.3
	Middle Manager	209	34.2
	Domain Specialist	168	27.5
	Analyst	117	19.1
Organization size	Fewer than 250 employees	146	23.9
	250–1,000 employees	221	36.1
	More than 1,000 employees	245	40.0
Governance maturity	Initial or developing	187	30.6
	Defined	229	37.4
	Managed	196	32.0

Table 3. Reliability, Convergent Validity and Collinearity Statistics

Construct	Items	Loading range	α	CR	AVE	VIF
TDP	4	0.829–0.885	0.877	0.915	0.730	1.76
IDA	4	0.842–0.877	0.889	0.924	0.752	1.94
AAC	4	0.830–0.880	0.887	0.922	0.747	1.88
ESC	4	0.826–0.890	0.886	0.921	0.745	1.90
POV	4	0.845–0.872	0.874	0.914	0.726	1.91
PDR	4	0.825–0.885	0.882	0.919	0.739	1.51
DTR	5	0.824–0.858	0.893	0.921	0.701	2.98

Construct	Items	Loading range	α	CR	AVE	VIF
TAD	4	0.822–0.874	0.865	0.908	0.712	1.73
VRL	4	0.827–0.872	0.877	0.915	0.730	1.68
SCM	4	0.817–0.879	0.864	0.908	0.711	1.60

Table 4. Heterotrait–monotrait ratios of correlations (HTMT)

	TDP	IDA	AAC	ESC	POV	PDR	DTR	TAD	VRL
TDP	—								
IDA	0.563	—							
AAC	0.586	0.624	—						
ESC	0.566	0.619	0.572	—					
POV	0.580	0.610	0.585	0.607	—				
PDR	-0.493	-0.487	-0.466	-0.503	-0.557	—			
DTR	0.629	0.654	0.660	0.652	0.645	-0.547	—		
TAD	0.522	0.507	0.549	0.481	0.493	-0.427	0.703	—	
VRL	0.473	0.535	0.483	0.554	0.452	-0.410	0.678	0.489	—
SCM	0.426	0.487	0.480	0.474	0.514	-0.394	0.666	0.503	0.476

Table 5. Structural Path Estimates, Significance and Effect Sizes

Hypothesis	Path	β	SE	*t*-value	*p*-value	f^2	Result
H1	TDP → DTR	0.157	0.036	4.36	< 0.001	0.032	Supported
H2	IDA → DTR	0.168	0.039	4.34	< 0.001	0.034	Supported
H3	AAC → DTR	0.202	0.037	5.48	< 0.001	0.051	Supported
H4	ESC → DTR	0.180	0.038	4.73	< 0.001	0.040	Supported
H5	POV → DTR	0.146	0.036	4.08	< 0.001	0.026	Supported
H6	PDR → DTR	−0.110	0.033	3.36	< 0.001	0.018	Supported
H7	HCDG → PDR	−0.563	0.028	20.32	< 0.001	0.464	Supported
H8	DTR → TAD	0.438	0.042	10.32	< 0.001	0.152	Supported
H9	DTR → VRL	0.410	0.045	9.08	< 0.001	0.130	Supported
H10	DTR → SCM	0.425	0.046	9.29	< 0.001	0.132	Supported

Table 6. Mediation Analysis of Indirect Effects Through Digital Trust

Indirect path	Indirect effect	95% CI	Direct effect	VAF (%)	Mediation type
TDP → DTR → TAD	0.069	[0.037, 0.106]	0.103	40.1	Complementary
IDA → DTR → TAD	0.074	[0.040, 0.113]	0.049	60.2	Indirect-only
AAC → DTR → TAD	0.088	[0.057, 0.125]	0.120	42.3	Complementary
ESC → DTR → TAD	0.079	[0.046, 0.118]	0.009	89.5	Indirect-only
POV → DTR → TAD	0.064	[0.032, 0.100]	0.034	65.2	Indirect-only
TDP → DTR → VRL	0.064	[0.035, 0.100]	0.046	58.3	Indirect-only
IDA → DTR → VRL	0.069	[0.036, 0.108]	0.121	36.4	Complementary
AAC → DTR → VRL	0.083	[0.052, 0.122]	0.025	77.2	Indirect-only
ESC → DTR → VRL	0.074	[0.043, 0.112]	0.162	31.3	Complementary
POV → DTR → VRL	0.060	[0.031, 0.094]	−0.026	n/a	Indirect-only
TDP → DTR → SCM	0.067	[0.037, 0.104]	−0.010	n/a	Indirect-only
IDA → DTR → SCM	0.071	[0.039, 0.107]	0.064	52.8	Indirect-only
AAC → DTR → SCM	0.086	[0.053, 0.126]	0.055	61.0	Indirect-only

Indirect path	Indirect effect	95% CI	Direct effect	VAF (%)	Mediation type
ESC → DTR → SCM	0.076	[0.043, 0.118]	0.043	63.8	Indirect-only
POV → DTR → SCM	0.062	[0.032, 0.097]	0.123	33.6	Complementary

Table 7. Permutation-Based Multi-Group Analysis of Selected Structural Paths

Path	Manufacturing	Financial	Healthcare	Public	Largest Δβ	*p*
TDP → DTR	0.101	0.052	0.280	0.172	0.228	0.122
IDA → DTR	0.041	0.146	0.219	0.199	0.178	0.380
AAC → DTR	0.157	0.289	0.188	0.183	0.132	0.603
ESC → DTR	0.284	0.173	0.081	0.244	0.203	0.247
POV → DTR	0.201	0.133	0.126	0.100	0.102	0.775
DTR → TAD	0.526	0.301	0.444	0.520	0.225	0.268

Table 8. Comparison of the Proposed Framework with Representative Prior Studies

Study	Governance dimensions	Empirical validation	Outcome linkage	Explained variance
Abraham et al. [18]	Conceptual, six domains	Systematic review only	Not modelled	Not reported
Alhassan et al. [19]	Activity-based taxonomy	Interviews (n = 12)	Not modelled	Not reported
Janssen et al. [20]	AI-focused, three elements	Illustrative cases	Conceptual only	Not reported
Shin [21]	Fairness, accountability, transparency	Survey (n = 362)	Trust only	$R^2 = 0.57$
Martin [24]	Contextual privacy norms	Experiment (n = 468)	Trust only	$R^2 = 0.41$
Proposed HCDG framework (Verma et al.)	Five specified dimensions and risk	Simulated data (n = 612), composite-based SEM	Three outcomes, mediated	$R^2 = 0.545$