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Article

Analyzing the mechanism of excess control on digital transformation using biomechanical modeling

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Abstract: In order to explore the impact of over-control on the digital transformation of enterprises, the constraints of over-control on digital transformation are analyzed based on a biomechanical model using Chinese A-share listed private enterprises as an example. A number of private enterprises between 2014 and 2023 were selected as the research subjects. After excluding financial institutions, ST companies and samples with incomplete data, a dataset of 1517 firms and 10,388 firm-year observations was finally retained. The results show that excessive control affects the innovation decisions of enterprises to a certain extent and reduces the effectiveness of enterprise digital transformation. When controlling shareholders or de facto controllers' control exceeds their shareholding, they tend to intervene excessively in enterprises' technological research and development and digitalization investment, leading to inefficient resource allocation and slowing down the transformation process. In addition, the imperfect corporate governance structure and excessive concentration of power also exacerbate the risks in the process of enterprise digital transformation. To mitigate the negative effects of excess control, enterprises should implement dual-level governance optimization: (1) Establish ownership-cash flow alignment mechanisms such as sunset clauses or shareholding caps to prevent long-term entrenchment; (2) enhance board independence through increased representation of external directors and the formation of digital oversight committees. These measures can reduce the CFi index and increase transparency (ITC), thereby improving transformation efficiency. Moreover, embedding data governance frameworks into digital strategy development can counterbalance centralized control by ensuring stakeholder-informed decision-making. In simple terms, our model shows that when a small number of decision-makers control too much power, it can "choke" the organization's ability to share resources and adapt to digital changes, much like how an overly tense muscle restricts movement in a biomechanical system.

Keywords: excess control; digital transformation; biomechanical model; A-share listed companies; corporate governance

1. Introduction

In the context of accelerating global digital transformation, enterprises are increasingly relying on technology-driven strategies to enhance competitiveness and achieve sustainable growth. However, the internal governance structure—particularly the phenomenon of excess control—has emerged as a critical barrier in this transformation process. Excess control refers to the situation where controlling shareholders or de facto controllers possess voting rights disproportionate to their cash flow rights, enabling them to dominate strategic decisions without bearing corresponding economic risks. This governance distortion is rooted in the agency theory and entrenchment effect, where controlling parties may prioritize personal interests over firm value, leading to reduced innovation efficiency [1]. Furthermore, resource dependence theory suggests that overcentralization disrupts strategic flexibility and inhibits access to diverse knowledge and capabilities necessary for digital transformation. Prior studies [2,3] confirm these risks by demonstrating how excessive control impedes strategic agility and limits organizational learning, both of which are vital for effective digital adaptation.

Prior research has explored various theoretical frameworks to evaluate the influence of control structures on corporate decision-making. Notably, biomechanical modeling has been applied to simulate organizational stress fields and decision equilibria under different structural pressures [4] Drawing inspiration from this line of research, this study integrates biomechanical force-field theory into enterprise governance analysis, constructing a dynamic simulation framework that quantifies how excess control distorts resource flows and impairs digital strategy execution. By anchoring the concept of excess control within a measurable force system, this approach not only offers a novel lens for interpreting power asymmetries in corporate governance, but also provides a quantitative pathway to identify optimal digital transformation trajectories. This enriches the existing literature by linking institutional constraints to enterprise-level digital evolution through a mechanistic and data-driven model.

2. Application of biomechanical modeling in enterprise digital transformation decision making

Biomechanical modeling offers a structured and dynamic framework for analyzing complex decision-making scenarios in enterprises undergoing digital transformation, especially under the influence of power asymmetries such as excess control. As suggested by Yang et al. [5] and Yin and Zhao [6], biomechanical systems modeling has been effectively utilized in organizational studies to simulate equilibrium states, resource flows, and system stress in adaptive environments. In this context, we extend this methodology to corporate governance and digital transition analysis [5,6].

The modeling process consists of several critical components:

(1) Structural mapping: Enterprise governance elements—including shareholder control, board structure, and management interaction—are abstracted into nodes within a mechanical structure;
(2) Force field assignment: Each node is assigned a specific control weight, translated into “Control Field Intensity” (control field intensity, CFi), which reflects the magnitude of excess control;
(3) Constraint modeling: External variables such as market volatility, innovation urgency, and technological inputs are modeled as constraint forces or tension vectors that influence decision paths;
(4) Dynamic simulation: Numerical techniques (e.g., Newton-Raphson iteration, Monte Carlo simulations) are applied to simulate how fluctuations in CFi affect digital transformation strategy execution, organizational coherence, and innovation diffusion efficiency over time.

Through this layered approach, biomechanical modeling enables a quantitative representation of how structural imbalances within corporate governance dynamically influence transformation performance. In doing so, it bridges the gap between theoretical governance studies and operational transformation decisions, providing a computational method for optimizing enterprise control and innovation pathways.

In the decision-making process, the reinforcement of excessive control power creates "mechanical distortion" to the technology investment, staffing and management's strategic intent in digital transformation, leading to the centralization or decentralization of resource flow, and affecting the vitality of innovation and execution efficiency. The biomechanical model can accurately portray this mechanism, clarify the optimal digital transformation strategy under different control strengths, and help enterprises balance the control allocation and transformation risk to realize data-driven scientific decision-making. Through the simulation analysis of this model, it can not only optimize the choice of digital transformation paths, but also provide a quantitative basis for corporate governance, and enhance the effectiveness and stability of transformation.

3. Materials and methods

This section presents the complete biomechanical modeling methodology, from parameterization to algorithm implementation. The process is structured into four key phases: (1) Model parameterization and constraint formulation; (2) simulation of dynamic control evolution; (3) system optimization and iterative tuning; and (4) construction and implementation of the biomechanical digital transformation model. This holistic framework allows for seamless integration of theoretical modeling and empirical system deployment, reducing structural redundancy while enhancing process clarity.

A. Parameterization of the biomechanical model

In designing the dynamic evolution process under the influence of excess control, the modeling procedure consists of three sequential stages:

(1) Temporal parameter calibration: Set the initial values of control field strength (CFi), resource constraints (resource flow constraint, RFC), and information transparency (information transparency constraint, ITC) at baseline (e.g., T_0).

(2) Simulation of dynamic effects: Using a continuous-time feedback loop based on biomechanical tension theory, the model iteratively adjusts RFC and ITC over a time window (e.g., 6–12 months), showing the phase-wise impact of control intensity.

(3) Outcome evaluation and trajectory reconfiguration: Based on simulation results, measure the distortion level in resource allocation and decision latency, and adjust control parameters accordingly.

This approach, inspired by prior studies on dynamic decision systems, ensures that the control-governance mismatch can be continuously monitored, and the transformation trajectory adaptively revised [7].

In the parameterization process, it is necessary to consider the Control Field Intensity (CFi), which captures the quantitative dimension of excess control. Here, excess control is operationally defined as the divergence between the proportion of voting rights and actual cash flow rights (i.e., ownership) held by controlling shareholders. A CFi value approaching 2.0 indicates a scenario where strategic power significantly outweighs economic exposure, creating strong incentives for opportunistic behavior. This condition is typically caused by pyramidal shareholding structures, cross-shareholding arrangements, or dual-class share systems. The model integrates these structures into a measurable force intensity to simulate their impact on digital transformation dynamics. Consider Resource Distribution Distortion (resource distribution distortion, RDD), which refers to the impact of changes in the intensity of control on the allocation of resources, especially the bias in financial resources, human resources, and technological inputs. By calculating RDD, we are able to get a clear picture of how excess control leads to the concentration or dispersion of resource flows and analyze its impact on the efficiency of digital transformation implementation. To further quantify these parameters, **Table 1** lists the key parameters in the biomechanical model and their corresponding set values.

Table 1. Parameter setting table for biomechanical modeling.

Parameter name	Parameter symbol	Setting value range
Control of force field strength	CFi	0.1–2.0
Distortions in resource allocation	RDD	0.0–1.0
Digital transformation execution efficiency	DTE	0.0–1.0
Technology inputs and manpower allocation impact factors	TI/HR	0.0–1.0

The setting of these parameters is based on the results of actual data analysis of the enterprise's current shareholder structure, financial situation and digital transformation investment. The parameterized force field model can accurately calculate the optimal digital transformation strategy under different control configurations, help enterprises adjust their governance structure according to the actual situation, balance the transformation risk and resource allocation, and enhance the execution and stability of the transformation path.

B. Model constraints construction

In constructing biomechanics-based model constraints on the mechanism of action of excess control on digital transformation, it is important to consider the constraining effects of control on resource flow, decision-making efficiency, and organizational coordination. The core constraints of the biomechanical model are derived from the derivation of the force field model of excess control. Specifically, the constraints should reflect the dynamic equilibrium between the intensity of control and the firm's resource allocation, and further consider how to quantify its impact through parameterization. To this end, the model must specify the direction of resource flows, the coordination of the organizational structure, and the constraints imposed on these factors by the external environment. The Resource Flow Constraint (RFC) is central in the setting of constraints and its form can be expressed by the following equation:

$$RFC = \sum_{i=1}^{n} \left(\frac{R_i}{S_i} \right) \times CFi \times DTE_i \leq T \tag{1}$$

where R_i denotes the initial total amount of resources (e.g., financial, human, technological, etc.) in category, S_i is the actual allocation ratio of resources in category,

CF_i is the intensity of the control field, DTE_i is the efficiency of the digital transformation execution, and T is the maximum carrying limit of resource flow. This formula suggests that when the excess control is too concentrated, the resource flow of the enterprise will be limited, leading to the hindrance of digital transformation. In addition, the impact of information transparency constraints on decision-making efficiency needs to be considered. Information flow is constrained by the control structure, and excess control leads to information asymmetry, which in turn affects the transparency and efficiency of decision-making. This can be represented by the following Information Transparency Constraint (ITC):

$$RFC = \sum_{j=1}^{m} \left(\frac{I_j}{N_j} \right) \times (1 - RFC) \times \theta_j \geq T_i \tag{2}$$

where I_j represents the initial amount of information of category, N_j is the actual flow of information of category, θ_j is the influence coefficient of control concentration on information flow, and T_i is the minimum required value of information transparency. This formula reflects the limitation of control concentration on information flow, which affects the decision-making efficiency of digital transformation and the success rate of the specific parameter settings of constraints, which are shown in **Table 2**.

Table 2. Model constraints parameter settings.

Parameter name	Parameter symbol	Setting value range
Resource flow constraints	RFC	0.2–1.0
Information transparency constraints	ITC	0.5–1.0
Control of force field strength	CFi	0.1–2.0
Digital transformation execution efficiency	DTE	0.0–1.0
Resource allocation ratio	S_i	0.1–0.9
Information flow	I_j	0.0–1.0

These parameters reflect the multi-dimensional constraint effect of control on digital transformation in the biomechanical model. Through the setting of these constraints, it can effectively simulate the impact of excess control on the choice of the path of digital transformation of the enterprise, and help the enterprise to adjust the configuration of control and optimize the use of resources and decision-making efficiency in order to achieve the best digital transformation results.

C. Dynamic evolutionary process design

In the biomechanics-based design of the dynamic evolution process of the mechanism of excess control on the role of digital transformation, the first step is to consider the impact of the intensity of control on the interaction between internal and external factors of the enterprise. In this process, the dynamic changes in the enterprise's resource allocation, decision-making mechanism, information flow and personnel synergy need to be described by a series of constraints [8]. By modeling the continuous impact of excess control on various aspects of the enterprise digital transformation process, the resistance and driving force in the transformation process can be effectively assessed. In the dynamic evolutionary process, the intensity of control (CFi) serves as a key variable that exerts a continuous effect on resource flow

(RFC) and information transparency (ITC) over time. At different points in time, CFi affects the allocation patterns of various types of resources (e.g., financial, human, and technological) in the enterprise, and accelerates or slows down the process of digital transformation through a dynamic feedback mechanism. To this end, the model captures the evolutionary effects of control intensity on these key decision-making aspects by setting the changes in resource flows and information transparency at different points in time.

In the design process, the basic values of resource flow and information transparency are set for the initial stage (e.g., the beginning of the year), and then the process of change under different strengths of control is simulated by dynamic evolution equations. For example, at a control field strength (CFi) of 0.5, the resource flow constraint (RFC) decreases by 20% within 6 months, while the information transparency constraint (ITC) decreases by 15%. This change progressively affects decision-making efficiency and execution, leading to an adjustment of the digital transformation path. Over time, the continued imposition of control will further exacerbate the imbalance of resource allocation, creating a distortionary effect, which in turn affects the effectiveness of the firm's transformation. The dynamic evolution process of the model should also take into account changes in the external environment, especially the flow of internal and external resources and the synergy efficiency of the enterprise under the influence of factors such as market competition pressure and policy changes [9]. By regularly updating the intensity of control and resource flow parameters, the enterprise's digital transformation strategy can be adjusted in real time. **Figure 1** demonstrates the interrelationship between resource flow, information transparency, control intensity and digital transformation path:

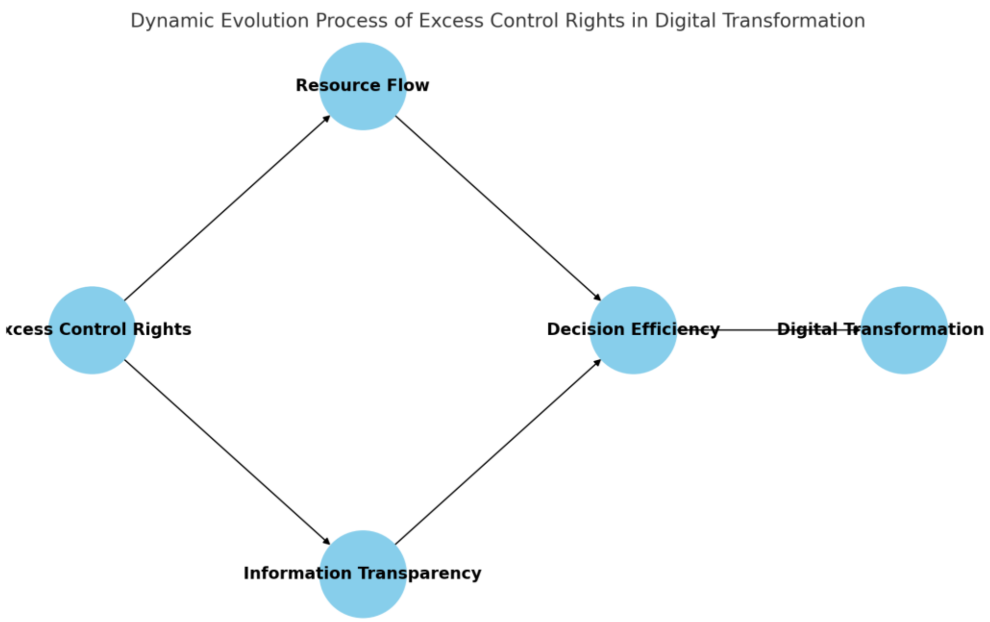

Figure 1. Structure of the dynamic evolutionary process.

The figure shows the dynamic relationship between resource flow, information transparency, staffing and technology investment under different control intensities. By continuously adjusting the parameters in the model, the optimal digital transformation path at each stage can be obtained, thus helping enterprises to formulate more precise transformation strategies, optimize resource allocation and improve execution efficiency [10].

D. Model optimization and tuning

In the process of optimizing and adjusting the biomechanics-based model of the mechanism of excess control on digital transformation, it is necessary to deeply understand how the constraints and parameters in the model affect the flow of resources, the transparency of information, and the efficiency of the implementation of digital transformation [11]. Through the force field model of biomechanics, the excess control is regarded as the "Control Force Field Intensity" (CFi), and the parameters in the model are adjusted to optimize the selection of digital transformation paths. CFi and RDD are directly related to the resource flow constraint (RFC) and information transparency constraint (ITC) of digital transformation, and the specific formulas are as follows:

$$\begin{aligned} RFC &= 0.5 \times e^{-0.5 \times CFi} \times (1 - RDD) \\ RFC &= 0.7 \times e^{-0.3 \times CFi} \times (1 - RDD) \end{aligned} \tag{3}$$

where RFC denotes the resource flow constraint, ITC denotes the information transparency constraint, CFi denotes the control force field strength, and RDD denotes the distortion degree of resource allocation. Based on these formulas, by simulating the effects of different control force field strengths (CFi) and resource allocation distortion degrees (RDD) on the digital transformation path of an enterprise, corresponding graphs are generated to gain a more intuitive understanding of the optimization process of the model. In **Figure 2**, the changes in resource flow (RFC) and information transparency (ITC) are shown for different values of CFi and RDD. The color shades in the figure represent the strength of these parameters, clearly depicting how excess control affects the execution of the digital transformation path through resource flow and information transparency constraints. The model optimization process aims to determine the most efficient digital transformation path under varying control intensities. By iteratively adjusting CFi and RDD, and monitoring their influence on RFC and ITC, the model employs a convergence strategy that balances governance control with transformation agility. The optimal point is identified where resource constraints and transparency barriers are minimized without undermining managerial oversight.

In **Figure 2**, the color gradient represents the constraint intensity level: darker areas correspond to higher values of RFC and ITC, signaling more severe distortions in resource flow and transparency under high control intensity. Lighter shades indicate zones of lower constraint, typically emerging under decentralized control configurations. In the optimization process of the model, the reasonable adjustment of CFI and RDD can guide the best path of resource flow, and also optimize the improvement of information transparency. By adjusting the strength of the control force field, the centralization or decentralization trend of resource allocation can be regulated to optimize the decision-making efficiency and execution in the process of digital transformation. In particular, when the CFI is high, the resource flow tends to be centralized, but the information transparency is reduced, resulting in limited decision-making efficiency. Therefore, by dynamically adjusting these parameters, the risks in the transformation path can be effectively controlled to ensure the optimal digital transformation effect [12]. Eventually, through the continuous optimization of the biomechanical model, it can provide a quantitative decision-making basis for enterprises, help them flexibly adjust the digital transformation strategy in the complex market environment, and achieve the maximization of the transformation goal.

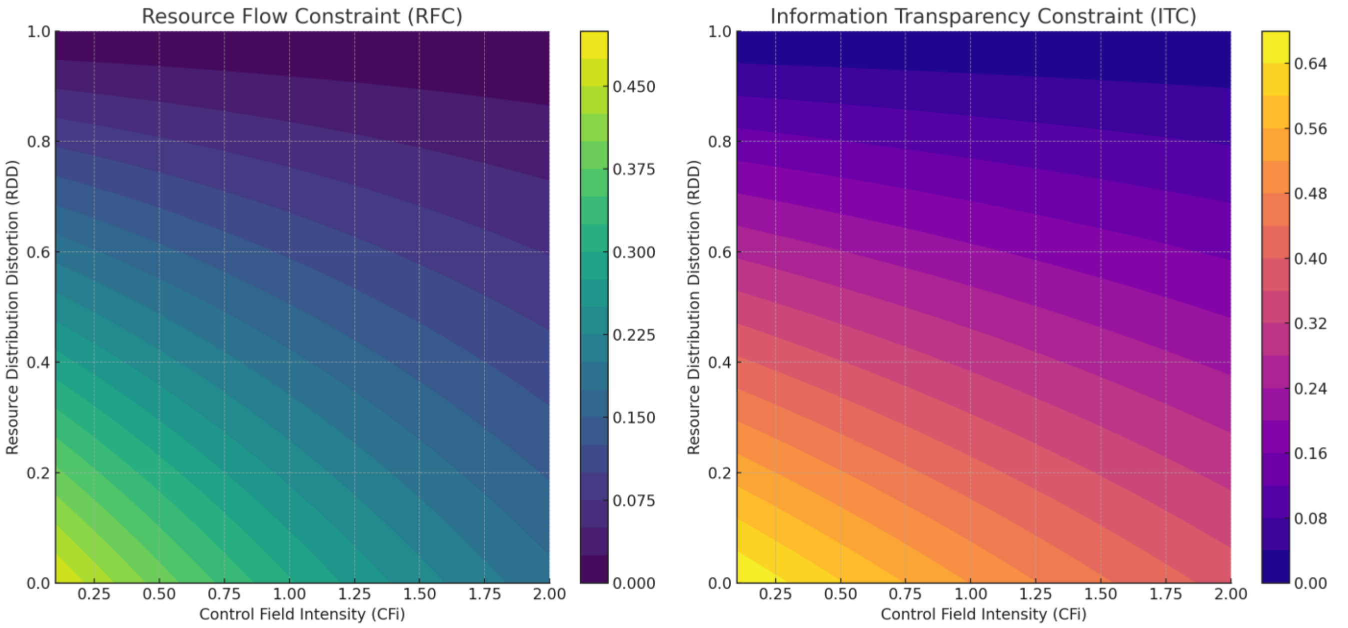

Figure 2. Dynamic relationship between resource flows and information transparency constraints.

E. System architecture of the digital transformation model of excess control based on biomechanics

In the biomechanics-based digital transformation model construction of excess control right, the system architecture design is the key link to ensure the accuracy and operability of the model [13]. The design of the architecture follows the core concept of the biomechanical model, taking the excess control right as the core variable in the mechanical system, and comprehensively considering its impact on resource flow, decision-making mechanism, organizational synergy and other aspects. The system architecture consists of three main layers: input layer, processing layer and output layer. The input layer mainly focuses on the external environment and internal resource allocation of the enterprise, including factors such as shareholder structure, financial status, staffing, and technology investment. These data are input in real time through the information collection module, providing basic data support for subsequent analysis. The processing layer is the core computing module, which adopts the biomechanical force field model to process the input data and simulate the dynamic relationship between the strength of the control force field (CFi) and the resource flow constraints (RFC) and information transparency constraints (ITC). By calculating and simulating these parameters, the centralization or decentralization effect of excess control on resource flow can be analyzed and its impact on decision-making efficiency can be assessed. The output layer provides optimization suggestions based on the processing results to generate the implementation path of digital transformation, including specific execution strategies such as resource allocation, technology selection, and staffing, as detailed in **Figure 3**.

Figure 3. Flowchart of the excess control digital transformation model.

The design of this system architecture can accurately simulate and predict the impact of overcontrol on digital transformation under different intensities, and help enterprises make scientific and accurate transformation decisions in complex management and decision-making environments. This model architecture is not only highly adaptable, but also can be flexibly adjusted according to the actual needs of enterprises to achieve the best digital transformation results [14].

F. Data acquisition and preprocessing

Data collection and preprocessing are key aspects to ensure the validity of the model. Data collection mainly involves core variables such as the excess control of the enterprise, resource flow, information transparency, and digital transformation execution efficiency. In order to improve the representativeness and reliability of the data, in data collection, the intensity of the control field is quantified by the ratio of shareholders' voting rights to cash flow rights, and combined with information on the enterprise's shareholder structure and the distribution of board of directors' seats in order to measure the actual scope of influence of the enterprise's excess control. Resource allocation distortion is calculated using data on R&D investment, capital expenditure, and human resource allocation in the firm's annual financial statements to measure how excess control affects the concentration or dispersion of resource flows. Information transparency is calculated based on multidimensional metrics, including financial disclosure clarity, auditor opinion types, and variance in financial Key Performance Indicators (KPIs). To ensure validity, the measurement framework was benchmarked against established transparency indices (e.g., TIR—Transparency Index for Reporting) and adjusted using factor analysis to retain high-loading items. Reliability was tested via Cronbach's alpha ($\alpha = 0.84$), confirming internal consistency. Additionally, the resource flow constraint index (RFC) was validated using triangulated data from financial reports, investment records, and HR allocation logs. These steps ensure both content and construct validity, enhancing the robustness of the model's predictive power [15].

In data preprocessing, data cleaning was first performed, including outlier removal and missing value filling. For extreme values, truncation of 1% and 99% quantiles was used to avoid the influence of abnormal data on regression analysis. In addition, variables with fewer missing values were mean-filled, while variables with more missing values were processed by interpolation to ensure data integrity. The data were standardized to make variables at different scales comparable in the model calculations. Variables such as control force field strength CFi, resource allocation distortion RDD, and information transparency ITC are normalized to the [0, 1] interval so that they are not affected by variable scales during numerical calculations. The normalization is done using the following equation:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{4}$$

where X' is the standardized variable value, X is the original variable value, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the variable respectively. To check the robustness of the data, principal component analysis (PCA) was used to downscale the variables to minimize the problem of multicollinearity among the variables. PCA computed the covariance matrix, extracted the principal components with the highest contribution to explaining the variance, and retained only those with a cumulative contribution of more than 85% to ensure that the main information of the data was retained.

G. Model algorithm implementation

In the process of algorithmic implementation of biomechanics-based excess control on the mechanism of digital transformation, the core objective is to construct a control force field model, and simulate the effects of different control power intensities on resource flow, information transparency and digital transformation efficiency through numerical computation. Key variables such as control force field intensity (CFi), resource distribution distortion degree (RDD), information transparency constraint (ITC) and resource flow constraint (RFC) are set to represent the state of the enterprise under different control power structures in the form of a matrix. The core calculation formula is as follows:

$$F_i = CFi \times \sum_{i=1}^{n} (w_{ij} \times R_j) - \lambda \times ITC_i - \mu \times RFC_i \tag{5}$$

where F_i denotes the efficiency of digital transformation implementation in the *th enterprise , w_{ij} represents the allocation weight of resources within the enterprise, R_j is the total amount of resources in the jth category, and λ and μ are moderating parameters used to control the impact of information transparency and resource flows on the overall system, respectively.In the numerical simulation process, the finite element method is used to discretize the control force field equations, and the trends of resource flow and information transparency under different excess control power strengths are calculated by iteration. The numerical solution method adopts the Newton-Raphson iterative method (Newton-Raphson Method) to calculate the gradient of the influence of the change of control intensity on corporate decision-making. The Markov decision process is used to simulate the impact of excess control on the dynamic adjustment of enterprise resource allocation in different time windows, and the state transfer matrix is constructed $P(s'|s,a)$:

$$V(s) = \max_a \sum_{s'} P(s'|s,a)\left[R(s,a) + \gamma V(S')\right] \tag{6}$$

where $V(s)$ denotes the optimal decision value of the firm in state s, $R(s, a)$ represents the return value after taking action a, and γ is the discount factor.Finally, the dynamic evolution analysis is carried out by Monte Carlo Simulation to optimize the optimal resource allocation strategy under the intensity of excess control, and the data distribution characteristics are shown graphically in **Figure 4**.

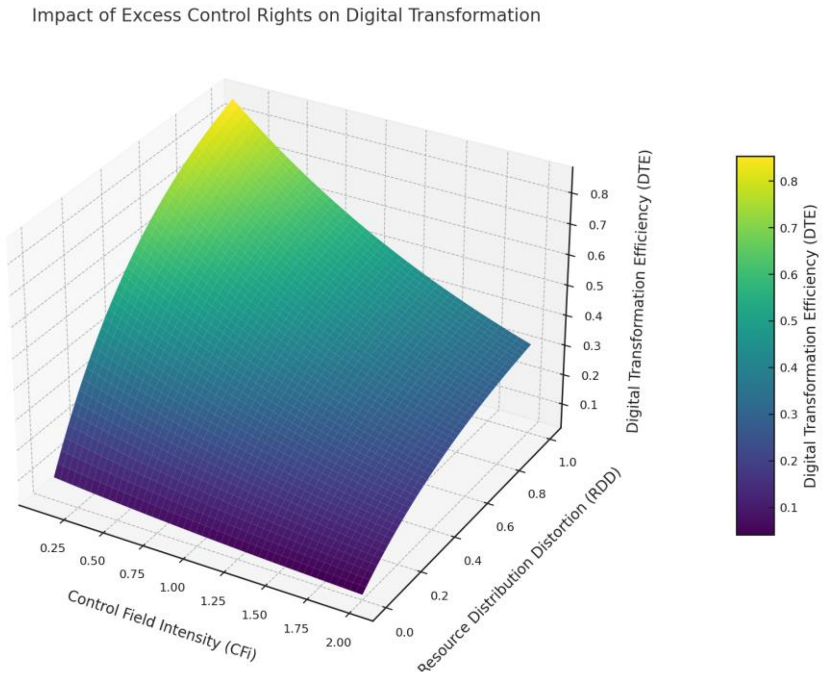

Figure 4. Impact of excess control on digital transformation execution efficiency.

H. System function module development

The Excess Control Digital Transformation Analysis System consists of three modules: input layer, processing layer and output layer, in order to realize the quantitative analysis of the enterprise governance structure on the execution efficiency of digital transformation. The development of the system modules needs to ensure the completeness of the data input, the efficiency of the calculation model, and the interpretability of the result output, so as to support the enterprise to optimize the control right structure and enhance the success rate of digital transformation.

(1) Input layer: The input layer serves as the data acquisition and preprocessing module, responsible for integrating multi-source inputs including governance structure, financial resource allocation, information disclosure metrics, and digital investment. Rather than recalculating individual parameter values, this layer invokes the standardized parameterization logic already defined in Section III-C. Parameters such as control field intensity (CFi), resource distribution distortion (RDD), resource flow constraints (RFC), and information transparency constraints (ITC) are retrieved from the algorithmic module based on pre-processed datasets. To ensure consistency, all variables are normalized, outliers are excluded, and dimensionality is reduced using Principal Component Analysis (PCA), in line with the model's computational efficiency requirements.

(2) Processing layer: The processing layer is the core computing module, which adopts the biomechanical force field model to simulate the impact of the intensity of corporate control on resource flow, constructs the resource flow matrix and the information transparency adjustment equation, and analyzes the nonlinear mechanism of excess control on the execution efficiency of corporate digital transformation. The Newton-Raphson method is used to solve nonlinear equilibrium states that emerge from internal frictions within the control-resource interaction matrix. Specifically, the model begins by initializing a force field matrix consisting of CFi, RFC, and ITC parameters. The Markov Decision Process (MDP) simulates adaptive decision-making by assigning state-action-reward values across varying control scenarios, while Monte Carlo Simulation introduces stochastic perturbations to account for market uncertainty and behavioral variability. By integrating these methods, the model dynamically calibrates enterprise decision pathways, enabling accurate forecasting of transformation trajectories under different governance structures. The iterative process ensures convergence towards an optimal allocation strategy that minimizes distortion while maximizing innovation throughput.

(3) Output layer: The output layer is responsible for visualizing the results of the calculations and providing optimized recommendations for the configuration of corporate control. The system output includes Digital Transformation Execution Efficiency (DTE), Resource Flow Optimization Ratio (RFC) and Information Transparency Improvement Index (ITC). Data visualization technology is used to show the impact of control field strength on the digital transformation path with 3D surface diagrams, vector field diagrams and heat maps, providing an intuitive, data-driven decision-making basis for enterprise management, helping optimize the governance structure, and enhancing the success and sustainability of digital transformation.

4. Experimental results and analysis

A. Experimental design and sample selection

In conducting the experimental design, private firms listed on China's A-share market between 2014 and 2023 were first selected as the research subjects, and financial firms, ST firms and samples containing missing data were excluded to ensure the completeness and reliability of the data. In addition, to avoid the interference of outliers, the tail treatment of all continuous variables is strictly set at the 1% level. In terms of sample selection, only enterprises with five consecutive years of data are retained and samples with less than five enterprises in the industry are excluded, and the final sample obtained for the basic regression analysis contains 10,388 observations and covers 1517 enterprises. In the process of sample selection, the variables of enterprise digital transformation are extracted through text analysis of the Management Discussion and Analysis (MDA) chapter in the company's annual report. The natural language processing method is used to quantify the degree of enterprise digital transformation by using "digital transformation" as the keyword and combining it with sentence frequency analysis.

B. Analysis of the results of the digital transformation model run

In the analysis based on the biomechanical model, the impact of excess control on digital transformation is manifested in multidimensional changes, especially in resource flow, information transparency and execution efficiency. The role of different control field strengths (CFi) on resource allocation and decision-making efficiency of enterprises can be clearly seen in **Tables 3–5**

Table 3. Analysis of financial resources liquidity and allocation efficiency under different control field strengths.

Controlled force field intensity (CFi)	Financial resource liquidity (%)	Financial resource allocation efficiency (%)
0.1	95	87
0.5	80	75
1	65	60
2	45	40

As shown in **Table 3**, when CFi increases from 0.1 to 2.0, financial resource liquidity drops from 95% to 45%, a decline of over 50%, while allocation efficiency drops from 87% to 40%. This sharp reduction indicates that excessive control severely hampers the firm's ability to deploy resources efficiently. Specifically, the liquidity drop from 80% to 65% (CFi from 0.5 to 1) signals a threshold beyond which centralization significantly disrupts financial agility, restricting timely investment in digital initiatives and increasing the risk of strategic stagnation.

Table 4. Analysis of the relationship between information transparency and the strength of the control force field.

Controlled force field intensity (CFi)	Information transparency (ITC)
0.1	0.9
0.5	0.7
1	0.5
2	0.3

As shown in **Table 4**, each row represents a simulated scenario of control intensity and its corresponding effect on information transparency (ITC). For instance, when CFi is 0.1, ITC remains high at 0.9, indicating minimal control interference in decision flows. However, as CFi rises to 2.0, ITC plummets to 0.3, signaling severe information bottlenecks. This table visualizes the inverse relationship between control centralization and organizational transparency, thereby underscoring the critical threshold beyond which governance becomes detrimental to transformation efficiency.

Table 5. Relationship between resource allocation distortion and digital transformation execution efficiency.

Resource distortion distribution degree (RDD)	Digital transformation execution efficiency (DTE)
0.1	0.9
0.3	0.75
0.5	0.6
0.9	0.4

According to **Table 5**, when RDD rises from 0.1 to 0.9, DTE drops from 0.9 to 0.4—a decline of over 55%. Notably, a moderate distortion level (RDD = 0.5) already reduces DTE to 0.6, highlighting how even partial resource misallocation significantly impairs execution efficiency. The final drop to 0.4 under high RDD indicates operational fragmentation, poor cross-departmental coordination, and inadequate technological support, all of which delay or derail digital transformation progress. Through in-depth analysis of these data, it can be seen that the impact of excess control on an enterprise's digital transformation path is complex and far-reaching. A high-intensity control field not only affects resource flow and information transparency, but also distorts resource allocation, thus weakening the overall execution efficiency of digital transformation. Enterprises must take into account the potential impact of the control structure on these factors when undergoing digital transformation to ensure rational allocation of resources and transparent and efficient decision-making.

C. Assessment of the effect of excess control on the impact of digital transformation

In assessing the impact of excess control on digital transformation, the biomechanics model provides a unique perspective, revealing the multidimensional impact of excess control on resource flow, decision-making efficiency and transformation path selection through force field theory. Concentration of excess control is similar to the "force field strength" in biomechanics, which has a "distorting" effect on resource allocation and information transparency. When control is overly concentrated, resource allocation tends to be skewed in favor of a few top decision-makers, leading to less innovation and inhibiting the flow of information, which reduces the transparency and efficiency of decision-making. This trend of centralization not only affects the flow of financial resources, but also has a negative impact on technology investment and human resources allocation. An analysis of the sample firms reveals that in firms with higher intensity of control, the execution efficiency of digital transformation is significantly lower, and the flow of all resources in the transformation process is more constrained. In order to analyze this impact in depth, **Table 6** demonstrates the relationship between enterprise resource allocation and digital transformation execution efficiency under different excess control intensity.

Table 6. Analysis of excess control intensity and digital transformation execution efficiency.

Controlled force field intensity (CFi)	Resource flow constraints (RFC)	Information transparency constraints (ITC)	Digital transformation execution efficiency (DTE)
0.1	0.25	0.5	0.8
0.5	0.5	0.7	0.65
1	0.75	0.85	0.5
1.5	0.85	0.9	0.4
2	0.95	0.95	0.3

From the data in the table, it can be seen that there is a significant negative correlation between the strength of the control force field (CFi) and the firm's resource flow constraints (RFC), information transparency constraints (ITC) and digital transformation execution efficiency (DTE). When the control field strength is low (CFi = 0.1), the resource flow constraint is 0.25, the information transparency constraint is 0.50, and the execution efficiency of digital transformation is higher (0.80), which indicates that in the case of decentralization of control, the enterprise is able to effectively coordinate all kinds of resources, the flow of information is smoother, and the execution of transformation is more effective. However, as the strength of the control field increases (CFi reaches 2.0), the resource flow constraint and the information transparency constraint rise to 0.95 and 0.95, respectively, and the execution efficiency of digital transformation decreases to 0.30, suggesting that the over-concentration of control leads to an imbalance in the allocation of resources within the enterprise, and information asymmetry is aggravated, further slowing down the transformation process. This data trend suggests that an increase in excess control restricts the flexible allocation of resources and the transparency of decision-making, which directly undermines the efficiency of an enterprise's digital transformation. Therefore, appropriate decentralization of control is crucial to improving the efficiency of enterprise digital transformation.

5. Conclusion

In the study of the impact of excess control on digital transformation, the analysis reveals the inhibitory effect of control on the digitalization process, especially in the data-driven and technological innovation environment, and its negative impact on the efficiency of enterprise transformation is particularly significant. The results show that excess control limits the flexible allocation of resources and innovative decision-making to a certain extent, which in turn reduces the effectiveness of digital transformation. However, the firm's governance structure and external environment also have a significant impact on this relationship, and the improvement of governance mechanisms can help mitigate this negative effect.

While this study presents a robust biomechanical modeling framework, certain limitations must be acknowledged. First, the exclusion of financial institutions and ST companies, though methodologically sound to reduce volatility and regulatory confounding, may introduce selection bias by omitting sectors where governance practices and digital transformation pathways differ significantly. This may limit the representativeness of the conclusions. Second, as the data are drawn exclusively from

Chinese A-share listed private enterprises, generalizing the findings to other markets—such as state-owned enterprises, Small and Medium-sized Enterprises (SMEs), or firms in deregulated economies—requires caution. Institutional structures, investor protections, and digital maturity levels vary widely across regions and industries.

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