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Firm digital transformation and corporate performance: The moderating effect of organizational capital☆

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A B S T R A C T

We use textual analysis to measure corporate digital transformation by the frequency of digital terms in the firm 10-K report. We then show that this digital transformation score (DGS) is associated with corporate value. Importantly, we show that organizational capital, the quality of corporate governance, information quality, and firm IPO age play non-negligible roles in shaping the value creation of corporate digital transformation. Our fresh evidence indicates that firms need to enhance their organizational capital, corporate governance, and firm information quality to benefit from their digital transformation efforts.

1. Introduction

CEOs increasingly prioritize growth and cost reduction as key value drivers (PwC, 2017), with digital transformation playing a central role.[1] A 2017 Gartner survey finds that 56 % of CEOs see digital improvements as catalysts for revenue growth and value creation. Digital transformation, defined as integrating information technologies like artificial intelligence, big data, cloud technology, and machine learning into a firm's processes and decision-making, aims to spur innovation-led growth and respond to the evolving needs of stakeholders such as employees and customers. This trend toward corporate digital transformation has recently attracted critical empirical attention to bear on economic implications of digital transformation.

Much of the existing evidence predominantly focuses on China and substantiates a positive correlation between digital transformation and various outcomes, including productivity (Guo et al., 2023; Zhang and Liu, 2023), corporate financial performance (Li et al., 2023b), ESG performance (Zhao and Cai, 2023), investment efficiency (Xu et al., 2023), stock liquidity (Liu and Liu, 2023), and reduced financial distress (Cui and Wang, 2023). Additionally, with a sample of Chinese companies, Wu et al. (2022), Chen and Xu (2023), Cui et al. (2023), and Lu et al. (2023) demonstrate that digital transformation is associated, respectively, with a reduction in stock price crash risk, cost stickiness, credit spread, and greenwashing tendencies.[2]

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[1] For instance, Zhang and Liu (2023) show that the digitalization has a positive effect on firms' centralization levels by decreasing their communication costs and improving their productivity.

[2] In a cross-country study, Daud et al. (2022) find that FinTech promotes financial stability via artificial intelligence, cloud technology, and data technology. Li and Pan (2022) show that digital transformation mitigates the adverse impact of organizational slack resources on innovation.

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Against this backdrop, the investigation into the economic implications of digital transformation beyond China, and the factors that mediate such relationships, remains an almost-untapped empirical research area. This study attempts to fill this important gap by increasing our understanding of the valuation effect of digital transformation and, notably, the role of organizational capital in a large sample of US firms. This research endeavor presents a rich scholarly opportunity, in part because despite evidence supporting the role of digital transformation in improving firm performance (e.g., Chen and Srinivasan, 2023), many firms still struggle with successful digital transformation. For instance, anecdotal evidence suggests that companies such as Kodak, Blockbuster, Nokia, BlackBerry, Target Canada, and Toys 'R' Us faced setbacks despite significant investments in digital transformation.[3] Relatedly, Rogers (2016) and McKinsey & Company (2019) emphasize that a significant number of companies fail in their digital transformation efforts. In academia, Marx et al. (2023) argue that the number of failed digital transformation activities is rising. Guo et al. (2023) show that digital transformation can decrease firm performance by increasing the operational cost rate, reducing total asset turnover, and increasing management expenses.

These observations beg the question of the mechanisms enabling firms to achieve innovation-led value creation. Extant related literature has been relatively unsuccessful in explaining these mechanisms. Our study addresses this significant gap in the literature by exploring how organizational capital shapes this valuation effect of digital transformation.[4] Organizational capital (OC) can be defined as "an agglomeration of technologies, business practices, process and designs, and incentive and compensation systems" (Lev and Radhakrishnan, 2005, p. 75). Recognized as a key driver of firm and national growth and competitiveness (e.g., Attig and El Ghoul, 2018; Lev and Radhakrishnan, 2005, Panta and Panta, 2023; Youndt et al., 2004, among others), it manifests in a firm's ability to appropriate and store knowledge in structures, processes, culture, and ways of doing business (Walsh and Ungson, 1991).

We posit that OC serves as the bedrock of an organization's ability to support the success of corporate digital transformation. This is because OC encompasses collective knowledge, skills, and a learning culture, which will likely facilitate effective technology adoption and enable superior innovation performance (e.g., Lev et al., 2009). In support of this prediction, McKinsey & Company (2019) reverse-engineered the failed efforts of digital transformation, suggesting that firms often neglect "procedural elements that make a transformation thrive" and fail to establish "the right change-management infrastructure," among other sources of failure. Fabac (2022) argues that firms should have systematic organizational support for the success of their digital transformation. Cui et al. (2021) emphasize that organizational capital is a crucial determinant of corporate innovation output. Pedersen (2022) suggests that organizational culture also plays a critical role in successfully leading an organization into the digital era because digital transformation transcends technology and business models. High OC will likely enhance firm's internal capabilities (e.g., employees and managerial skills, processes) as well as its external resources (e.g., commitments to regulations, meeting stakeholders' expectations) in minimizing risks associated with digital transformation, supporting firm's digital improvements, improving its information quality, and minimizing its financing frictions. This, in turn, will strengthen the value creation of firm's digital transformation.

We draw our main conclusions by adopting two approaches. First, following Chen and Srinivasan (2023), we measure a firm's digital activities through digital-related terms in its 10-K reports. Second, in line with Eisfeldt and Papanikolaou (2013), we assess OC by capitalizing firm's selling, general, and administrative expenses using the perpetual inventory method. Our findings indicate a robust and positive relationship between firm's digital transformation and corporate value. However, innovation-led value creation is significant, primarily in high OC firms. Our analysis also suggests that governance quality (e.g., higher institutional ownership) and information quality (e.g., more liquid stocks, higher analyst coverage) have a heterogeneous effect on the valuation of corporate digital transformation.

The paper proceeds as follows. Section 2 describes the sample and variable definitions. Section 3 discusses the methodology and empirical findings. Section 4 concludes with the research's findings.

2. Data and methodology

2.1. Data and sample

We download 10-K reports from Loughran–McDonald Textual Analysis Resources (https://sraf.nd.edu/sec-edgar-data/). We match firm names to Compustat. Our study removes financial (SIC 6000−6999), utilities (SIC 4900−4999), and governmental (SIC 9000 and above) entities. Following related literature (e.g., Chen and Srinivasan, 2023), we focus on the digital activities of non-tech firms to avoid the inherent bias of tech firms in digital activities.[5] These filters result in a final sample of 21,913 firm-year observations, covering the period 2011–2020. To minimize the influence of outliers, we winsorize non-categorical control variables at the 1% level at each tail of our sample.

[3] While we do not assert a direct causal link between digital transformation investments and failure, they likely played a contributing role.

[4] To be sure, Zhang et al. (2023) present one of the first studies, to our knowledge, on the role of business model innovation in bridging the gap between corporate performance and digital transformation.

[5] We exclude from our sample firms operating the industries with the following SIC codes: 3570, 3571, 3572, 3575, 3576, 3577, 3578, 3579, 3661, 3663, 3669, 3670, 3672, 3674, 3675, 3675, 3677, 3678, 3679, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7376, 7377, 7378 and 7379.

2.2. Digital transformation score

To construct the digital transformation score (DGS), we analyze the 10-K reports of our sample firms and count the frequency of digital terms (Chen and Srinivasan, 2023). We focus on 10-K reports as they often emphasize strategic shifts. As such, we expect a firm's digital advancements and its progression toward digital transformation to manifest in the form of digital transformation-related keywords in the disclosures of its annual report. To develop our dictionary of digital transformation–related keywords, we combine dictionaries developed by recent studies (Chen and Srinivasan, 2023; Huang et al., 2023; Li et al., 2023a; Teng et al., 2022; Zhang and Zhao, 2023; Zhong and Ren, 2023) to form a comprehensive wordlist. We then review the wordlist and retain 120 keywords, presented in the Appendix, covering analytics, automation, artificial intelligence, cloud computing, machine learning, digitization, and big data.

We use Python to conduct our textual analysis. Specifically, we employ regular expressions (regex) for text pattern recognition (for each keyword in our wordlist) and count the frequency of digital terms as in Chen and Srinivasan (2023). This frequency is our proxy for a firm's digital transformation score (DGS). Fig. 1 illustrates the DGS's upward trend during our sample period, corroborating findings from related studies.

2.3. Organization capital (OC)

We adopt Eisfeldt and Papanikolaou's (2013) approach to measure organizational capital by capitalizing selling, general, and administrative (SG&A) expenses using the perpetual inventory method.[6] Specifically, for firm *i* at time *t*, we calculate the stock of organizational capital (*OC*) as follows:

$$OC_{it} = (1-\delta_0) \times OC_{it-1} + \frac{SG\&A_{it}}{cpi_t}, \tag{1}$$

where *SG&A* is selling, general, and administrative expenses, *cpi* is the consumer price index, and δ_0 is the depreciation rate of organization capital, which is set to 15 %. Due to the recursive nature of this model, the initial observation (OC_0) is indeterminate. We define it as:

$$OC_0 = \frac{SG\&A_1}{g+\delta_0}, \tag{2}$$

where *g* is the real growth rate of *SG&A*, assumed to be 10 %. Following Eisfeldt and Papanikolaou (2013), we deflate organization capital by total assets.

3. Methodology and results

3.1. Does OC hinder or enhance corporate value?

We start our empirical analysis by addressing whether OC creates value. To this end, we run the following model:

$$TOBINSQ_{i,j,t} = \alpha_0 + \alpha_1 DGS_{i,t} + \alpha_2 FIRMCTRL_{i,t} + \varepsilon_{i,t},$$

where *i* denotes individual firms, *j* denotes industries, *t* denotes years. Following McLean et al. (2012), Rauh (2006), and Baker et al. (2003), we estimate *TOBINSQ* as the market value of equity minus the book value of equity plus the book value of assets, all scaled by the book value of assets. We also use future (i.e. next year) TOBINSQ in our robustness tests.

In our model, *FIRMCTRL* represents a set of firm-level control variables: firm size (*SIZE*), measured by the natural logarithm of total assets; leverage ratio (*LEVR*), measured by the ratio of total debt to total assets, to control for resource availability (Brammer and Millington, 2008); research and development expenses (*RD*), scaled by assets to account for asset specificity and intangibility; capital intensity (*CINT*), the ratio of net property, plant, and equipment divided by total assets to account for the effect of capital-intensive industries; dividend payment (*DIVD*), an indicator variable that equals one if a firm pays cash dividends on common equity and zero otherwise, to account for financial constraints and resource availability; institutional ownership (*IOWN*) to control for corporate governance quality; firm age (*AGE*); and sales growth (*SGR*), the year-over-year sales change ratio, to control for growth opportunities. We control for industry effects defined at the two-digit SIC level (μ_j) and year fixed effects (μ_t).

Panel A of Table 1 provides descriptive statistics for our main variables used in our baseline regression. Panel B reports the correlation matrix. The Pearson correlation coefficients are generally low, indicating minimal multicollinearity concerns in our regression analysis.

We then report our regression results in Table 2. We run two specifications: in the first (column 1), we present the regression results without time-variant firm characteristics. In the second (column 2), we augment our model with time-variant firm characteristics. Notably, in both models, the *DGS* coefficient is positive and significant at the 1 % level, suggesting that investors perceive digital transformation as beneficial to firm value. In column 3, where we cluster errors at the firm level, the *DGS* coefficient remains positive

[6] Lev et al. (2009) and Eisfeldt and Papanikolaou (2013) argue that a substantial portion of SG&A comprises expenses related to labor, IT, and other relevant costs in building a firm's organizational capital.

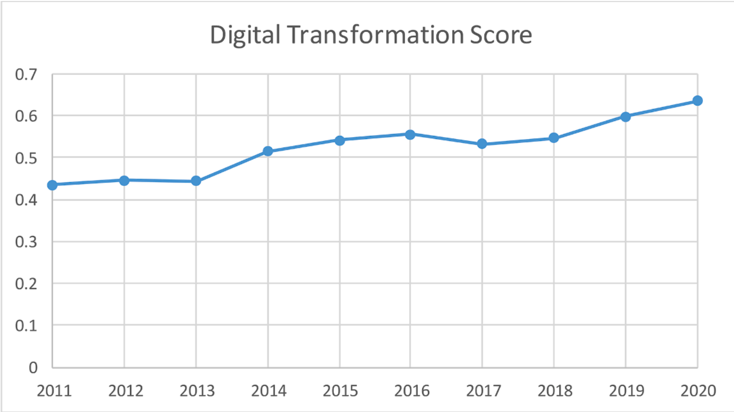

Fig. 1. This figure depicts the annual average frequency of digital transformation keywords in the 10-Ks over our sample period.

Table 1
Descriptive statistics for key variables.

Panel A: Descriptive Statistics										
	TOBINSQ	*DGS*	*SIZE*	*LEVR*	*RD*	*CINT*	*DIVD*	*IOWM*	*AGE*	*SGR*
Mean	2.2	0.45	6.58	0.27	0.07	0.27	0.44	0.55	2.9	0.07
p25	1.17	0.08	5.06	0.06	0	0.07	0	0.17	2.3	-0.08
p50	1.6	0.19	6.63	0.24	0	0.18	0	0.65	3	0.03
p75	2.49	0.47	8.06	0.41	0.04	0.4	1	0.88	3.5	0.14
SD	1.76	0.73	2.12	0.24	0.17	0.25	0.5	0.36	0.8	0.69

Panel B: Correlation Matrix										
	TOBINSQ	*DGS*	*SIZE*	*LEVR*	*RD*	*CINT*	*DIVD*	*IOWM*	*AGE*	*SGR*
TOBINSQ	1									
DGS	0.00	1								
SIZE	-0.20	0.03	1							
LEVR	-0.06	-0.04	0.31	1						
RD	0.42	-0.07	-0.42	-0.12	1					
CINT	-0.24	-0.17	0.22	0.26	-0.29	1				
DIVD	-0.11	-0.02	0.39	0.06	-0.25	0.15	1			
IOWM	0.01	0.05	0.44	0.03	-0.17	-0.04	0.09	1		
AGE	-0.16	-0.03	0.37	0.00	-0.30	0.06	0.37	0.205	1	
SGR	0.06	0.00	0.03	0.02	-0.02	-0.01	-0.02	0.04	0.00	1

Panel A of this table presents the descriptive statistics of our key regression variables. Our test variable is *DGS*, a firm's digital score, calculated by the ratio of digital keywords to the total words in the firm's annual report. Panel B reports the correlation matrix among our main variables: Tobin's Q (*TOBINSQ*), firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). All continuous variables are winsorized at the 1 % and 99 % levels.

and significant.

We next run robustness tests to validate the evidence of a positive association between *DGS* and *TOBINSQ* and report the results in Table 3. While our empirical setting does not provide a natural experiment allowing us to attribute causality to our results, we attempt to limit the endogeneity bias by repeating our analysis after replacing *TOBINSQ* with future *TOBINSQ* as the dependent variable. Across all specifications, as shown in columns 1–3, the positive and significant *DGS* coefficient reinforces the value-creating impact of digital transformation. So far, in our regression models, we control only for time and industry fixed effects. In columns 4 (TOBINSQ) and 5 (future *TOBINSQ*), we control for firm fixed effects to account for unobserved time-invariant heterogeneity across different firms. Including firm-fixed effects limits the endogeneity bias arising from omitting unobservable heterogeneity. We also include industry x year fixed effects and cluster the errors at the firm level. Related results, reported in columns 4 (TOBINSQ) and 5 (Future TOBINSQ) show that the *DGS* coefficient remains positive and significant at 10%. Caution is however merited in interpreting these results because firm fixed effects absorb much of the cross-sectional variation.[7]

Having established that firm digital transformation correlates with enhanced corporate value, we now focus on the influence of OC in this dynamic, as detailed in Table 4. We categorize firms into two groups: those with high OC (above the sample median) and those with low OC (below the sample median). Our findings, reported in columns 1 and 2, reveal that the positive link between *DGS* and

[7] In unreported results, we categorize the 120 keywords into the following groups: AI, blockchain, cloud computing, big data, digital technology, and others. Results are available upon request. We thank an anonymous reviewer for this suggestion.

Table 2
Digital transformation and corporate value.

	(1) TOBINSQ	(2) TOBINSQ	(3) TOBINSQ
DGS	0.121***	0.069***	0.069**
	(6.764)	(4.039)	(2.008)
SIZE		-0.058***	-0.058***
		(-8.363)	(-3.550)
LEVR		0.263***	0.263*
		(5.465)	(1.915)
RD		3.158***	3.158***
		(39.103)	(14.542)
CINT		-0.932***	-0.932***
		(-14.829)	(-6.022)
DIVD		0.175***	0.175***
		(7.200)	(3.638)
IOWM		0.531***	0.531***
		(15.709)	(7.969)
AGE		-0.085***	-0.085***
		(-5.586)	(-2.875)
SGR		0.156***	0.156***
		(10.339)	(5.980)
Constant	2.145***	2.368***	2.368***
	(158.050)	(42.130)	(18.985)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Clustered Errors	NO	NO	YES
Observations	21,913	21,910	21,910
R-squared	0.165	0.255	0.255

This table reports the results of multivariate regression analysis examining the link between a firm's *DGS* and corporate value, measured by Tobin's Q (*TOBINSQ*). We control for the following variables: firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). We control for industry and year-fixed effects in all our regression specifications. Column 3 clusters the standard errors at the firm level. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3
Robustness checks.

	(1) Future TOBINSQ	(2)	(3)	(4) TOBINSQ	(5) Future TOBINSQ
DGS	0.106***	0.063***	0.063**	0.051*	0.049*
	(6.069)	(3.688)	(1.969)	(2.157)	(2.124)
SIZE		-0.041***	-0.041***	-0.373***	0.117***
		(-5.961)	(-2.629)	(-5.521)	(3.392)
LEVR		0.223***	0.223*	-0.165*	-0.141
		(4.677)	(1.746)	(-1.951)	(-1.503)
RD		2.266***	2.266***	1.659***	0.065
		(28.400)	(11.711)	(15.003)	(0.326)
CINT		-0.908***	-0.908***	-0.728***	-0.759***
		(-14.628)	(-6.013)	(-4.508)	(-5.547)
DIVD		0.120***	0.120***	0.098*	0.080**
		(5.021)	(2.585)	(2.169)	(2.594)
IOWM		0.535***	0.535***	0.395***	0.596***
		(16.007)	(8.202)	(10.273)	(9.345)
AGE		-0.032**	-0.032	-0.637***	-0.060
		(-2.138)	(-1.139)	(-3.261)	(-0.573)
SGR		0.312***	0.312***	0.089***	0.203***
		(20.839)	(11.597)	(6.520)	(6.649)
Constant	2.095***	2.128***	2.128***	6.343***	1.383**
	(158.627)	(38.320)	(17.965)	(6.828)	(2.844)
Industry FE	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	NO	NO
Clustered Errors	NO	NO	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES
Industry x Year FE	NO	NO	NO	YES	YES
Observations	21,913	21,910	21,910	21,529	21,529
R-squared	0.147	0.216	0.216	0.750	0.696

In this table, we report results of robustness tests. In columns 1 through 3 we use future (i.e. next year) *TOBINSQ* as the dependent variable. In all our model specifications, we control for firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). In columns 4 and 5, we control for firm-fixed effects. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TOBINSQ is observable predominantly in high OC firms. To ascertain the role of OC, we include *OC* and its interaction with *DGS* (*OC* × *DGS*) into our main regression model. This analysis, showing a positive and significant interaction effect, supports the premise that OC amplifies the value creation from corporate digital transformation. In columns 4–6, we replicate this analysis using future TOBINSQ as the dependent variable and confirm our findings on the relevant role of OC in shaping the relationship between *DGS* and *TOBINSQ*.

We use *TOBINSQ* to measure corporate value because it is a market-based, forward-looking measure of firm performance that is risk-adjusted, captures investors' future expectations, and reflects the market's valuation of the firm's future profit prospects, thereby guiding investment decisions (Chappell and Cheng, 1982). In an additional test, we examine the impact of DGS on firm operating performance, measured by its return on assets (ROA). We report the results in Table 5. In columns 1–3, we reproduce the analysis of Table 2 and document a positive estimated coefficient of DGS. However, the effect of DGS on ROA appears significant only in column 2 (at 10 %), indicating a weak and inconsistent effect of corporate digital transformation on operating performance. This should not come as a surprise because the effects of corporate digital initiatives are associated with increased implementation costs and their effects on operating performance are inherently long-term. Interestingly, these findings align, to a large extent, with Chen and Srinivasan's (2023) evidence that differences in profit margins and sales growth between firms with digital activity and their peers are insignificant. Relatedly, Guo et al. (2023) find that the implementation of digital transformation can decrease firm performance by increasing operational costs.

Of more relevance to the focus of our study, we report in columns 4–6 the effect of OC in moderating the effect of DGS on ROA. Specifically, we replicate the analysis presented in Table 4, replacing TOBINSQ with ROA. Notably, we uncover a positive and significant effect of DGS on ROA, but exclusively in firms with high OC (refer to column 1). Strengthening this observation, the interaction variable (DGS x OC) is found to be positive and significant (at 5 %). This newly acquired evidence reinforces our earlier findings, suggesting that OC plays a pivotal role in amplifying the valuation effects of corporate digital transformation.

Taken together, our evidence indicates that organizational capital plays a crucial role in enhancing the valuation effect of corporate digital transformation. This finding, though novel, should not surprise us, as digital transformation involves the application of digital capabilities and technical innovations across all aspects of business. This includes processes, strategies, revenue models, customer engagement, risk management, assets, operations, products, and services, aiming to improve efficiency and create value. KPMG's 2023

Table 4
The moderating role of organizational capital.

	(1) *TOBINSQ* High *OC*	(2) Low *OC*	(3) Full Sample	(4) Future *TOBINSQ* High *OC*	(5) Low *OC*	(6) Full Sample
DGS	0.107**	-0.026	-0.017	0.094**	-0.015	-0.027
	(2.233)	(-0.715)	(-0.469)	(2.051)	(-0.448)	(-0.830)
High OC			0.102			-0.021
			(1.628)			(-0.359)
DGS x High OC			0.166***			0.179***
			(3.193)			(3.565)
SIZE	-0.040*	-0.187***	-0.086***	-0.028	-0.100***	-0.051***
	(-1.657)	(-5.870)	(-4.583)	(-1.241)	(-3.343)	(-2.897)
LEVR	-0.187	0.635***	0.258*	-0.191	0.572***	0.225*
	(-0.909)	(3.828)	(1.884)	(-0.988)	(3.719)	(1.771)
RD	6.114***	2.672***	3.130***	5.783***	1.790***	2.245***
	(6.735)	(11.605)	(14.388)	(6.366)	(8.853)	(11.586)
CINT	-0.270	-1.177***	-0.896***	-0.228	-1.275***	-0.903***
	(-1.254)	(-5.684)	(-5.797)	(-1.143)	(-6.145)	(-5.958)
DIVD	0.132**	0.229***	0.181***	0.096	0.200***	0.127***
	(2.080)	(3.414)	(3.787)	(1.571)	(3.025)	(2.726)
IOWM	0.250***	0.984***	0.517***	0.264***	0.873***	0.529***
	(3.048)	(8.890)	(7.767)	(3.361)	(8.064)	(8.132)
AGE	-0.046	-0.146***	-0.094***	-0.042	-0.016	-0.033
	(-1.155)	(-3.461)	(-3.178)	(-1.102)	(-0.406)	(-1.169)
SGR	0.611***	0.117***	0.163***	0.758***	0.259***	0.314***
	(6.442)	(4.355)	(6.225)	(8.539)	(9.417)	(11.639)
Constant	2.148***	3.102***	2.517***	2.017***	2.420***	2.198***
	(9.885)	(15.797)	(19.091)	(9.959)	(13.317)	(17.710)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Clustered Errors	YES	YES	YES	YES	YES	YES
Observations	11,081	10,828	21,910	11,081	10,828	21,910
R-squared	0.239	0.288	0.257	0.243	0.237	0.218

In this table, we examine the extent to which a firm's organizational capital shapes the effect of *DGS* on *TOBINSQ*. We use Eisfeldt and Papanikolaou's (2013) measure of organization capital (OC). In columns 1–3, *TOBINSQ* is the dependent variable, whereas in columns 4–6, future (i.e. next year) *TOBINSQ* is the dependent variable. In all our model specifications, we control for firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). In all our regression specifications, we control for industry and year fixed effects. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Digital transformation and operating performance (ROA).

	(1)	(2)	(3)	(4)	(5)	(6)
	Effect of DGS on ROA			OC role in moderating the effect of DGS on ROA		
	ROA	ROA	ROA	High *OC*	Low *OC*	Full Sample
DGS	-0.005	0.004*	0.004	0.010***	0.000	-0.003
	(-1.530)	(1.704)	(1.033)	(3.049)	(0.027)	(-0.528)
High OC						-0.043***
						(-6.297)
DGS x High OC						0.016**
						(2.463)
SIZE		0.037***	0.037***	0.015***	0.077***	0.042***
		(41.033)	(16.926)	(7.502)	(14.533)	(16.069)
LEVR		-0.198***	-0.198***	-0.131***	-0.250***	-0.195***
		(-31.891)	(-12.817)	(-7.752)	(-11.530)	(-12.681)
RD		-1.301***	-1.301***	-1.059***	-1.223***	-1.300***
		(-125.263)	(-47.090)	(-12.103)	(-39.551)	(-47.202)
CINT		0.042***	0.042**	0.010	-0.004	0.032*
		(5.261)	(2.472)	(0.707)	(-0.170)	(1.880)
DIVD		-0.001	-0.001	0.017***	0.005	-0.001
		(-0.340)	(-0.206)	(3.705)	(0.568)	(-0.147)
IOWM		0.067***	0.067***	0.037***	0.028**	0.070***
		(15.446)	(10.274)	(6.132)	(2.217)	(10.524)
AGE		0.020***	0.020***	0.003	0.050***	0.023***
		(10.505)	(5.884)	(1.213)	(8.402)	(6.600)
SGR		0.029***	0.029***	0.052***	0.022***	0.028***
		(15.053)	(7.398)	(5.130)	(5.402)	(7.010)
Constant	-0.087***	-0.297***	-0.297***	-0.088***	-0.540***	-0.319***
	(-34.511)	(-41.023)	(-16.401)	(-5.347)	(-16.000)	(-16.143)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Clustered Errors	YES	YES	YES	YES	YES	YES
Observations	21,913	21,910	21,910	11,081	10,828	21,910
R-squared	0.206	0.659	0.659	0.379	0.669	0.661

This table reports the results of multivariate regression analysis examining the link between a firm's *DGS* and operating performance (ROA). We control for the following variables: firm size (*SIZE*), leverage ratio (*LEVR*), research and development expenses (*RD*), capital intensity (*CINT*), dividend payment (*DIVD*), institutional ownership (*IOWN*), firm age (*AGE*), and sales growth (*SGR*). We control for industry and year-fixed effects in all our regression specifications. Column 3 clusters the standard errors at the firm level. In columns 4–6, we investigate the role of OC in moderating the association between DGS and ROA. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

survey of 2100 executives from 16 countries (p. 23) indicates that while corporate digital transformation remains vital for business growth, "culture, collaboration, and communication are the bottlenecks sabotaging successful transformation." These observations underscore the relevance of organizational capital in the success of corporate digital transformation. OC, described at the outset as "an agglomeration of technologies, business practices, processes and designs, and incentive and compensation systems" (Lev and Radhakrishnan, 2005, p. 75), is likely to not only foster a culture of learning and adaptation to technical innovations but also engage employees, guide strategic alignment, and facilitate effective risk management to navigate the complexities of digital initiatives.

As such, organizational capital will ensure that firms embrace technological change and thrive in the dynamic landscape of digital transformation, ultimately leading to value creation. We validate this prediction by documenting a positive association between DGS and corporate value, whether measured using TOBINSQ or ROA.

In a final test, and in order to further understand the relationship between *DGS* and *TOBINSQ*, we explore the influence of other firm-level characteristics, with results presented in Table 6. We start by examining the impact of institutional ownership, a measure of firm governance quality. Firms with strong governance structures are more likely to derive benefits from digital transformation. This is because, all else being equal, good corporate governance, such as increased institutional ownership, is associated with enhanced monitoring, reduced managerial agency problems, more efficient use of corporate resources, and diminished financing frictions (e.g., Shleifer and Vishny, 1986; Hartzell and Starks, 2003; Chung et al., 2002). Due to their nature, institutional investors possess an informational advantage derived from their ability to conduct quality research and efficiently collect and process corporate information (Attig et al., 2012). This advantage is likely to enhance the planning, execution, and oversight of digital initiatives. Consistent with this expectation, the results of our analysis, shown in columns 1 and 2, indicate that the positive relation between *DGS* and *TOBINSQ* primarily occurs in firms with high institutional ownership.

Subsequently, we assess the role of firm information quality using two proxies. First, employing Roll's (1984) average bid-ask spread over the fiscal year, we find, as depicted in columns 3 and 4, that DGS significantly and positively affects TOBINSQ in firms with a low bid-ask spread (i.e., low stock illiquidity). Furthermore, we analyze the effect of analyst coverage, observing a positive link between DGS and TOBINSQ in firms with a higher analyst following. These findings indicate that enhanced information quality amplifies the valuation impact of corporate digital transformation. This is plausible since, with reduced information asymmetry,

Table 6
The Mediation of Corporate Governance and Information Quality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Institutional Ownership		Bid-Ask Spread		Number of Analysts		IPO Age	
	High	Low	High	Low	High	Low	High	Low
DGS	0.131**	0.007	-0.011	0.121**	0.170***	-0.008	0.073	0.102**
	(2.517)	(0.197)	(-0.380)	(2.103)	(2.845)	(-0.256)	(1.237)	(2.026)
SIZE	-0.055**	-0.074***	-0.232***	-0.237***	-0.144***	-0.172***	0.024	-0.049*
	(-2.203)	(-3.487)	(-8.005)	(-8.268)	(-5.270)	(-6.032)	(0.824)	(-1.664)
LEVR	-0.083	0.512***	0.620***	-0.187	0.039	0.435***	-0.032	0.358
	(-0.371)	(3.142)	(4.560)	(-0.847)	(0.187)	(2.860)	(-0.152)	(1.587)
RD	4.959***	2.871***	2.633***	5.533***	3.372***	2.757***	3.794***	2.954***
	(10.387)	(11.976)	(11.502)	(10.338)	(7.929)	(11.248)	(8.267)	(9.799)
CINT	-0.593***	-1.179***	-0.949***	-0.705***	-0.627**	-1.028***	-0.973***	-0.577***
	(-2.796)	(-5.939)	(-6.167)	(-2.953)	(-2.557)	(-6.089)	(-3.381)	(-2.645)
DIVD	0.105	0.280***	0.239***	0.069	0.057	0.312***	0.175**	-0.062
	(1.607)	(4.400)	(4.596)	(1.016)	(0.815)	(5.700)	(2.106)	(-0.740)
IOWM	0.568**	0.363***	0.424***	-0.074	0.239***	0.421***	0.489***	0.679***
	(2.473)	(3.226)	(5.316)	(-0.789)	(2.722)	(4.602)	(3.759)	(5.974)
AGE	-0.043	-0.087**	-0.139***	-0.022	0.035	-0.091**	0.003	-0.176**
	(-1.129)	(-2.152)	(-3.861)	(-0.542)	(0.856)	(-2.296)	(0.021)	(-2.401)
SGR	0.223***	0.114***	0.096***	0.221***	0.166***	0.128***	0.416***	0.111***
	(4.667)	(3.702)	(3.572)	(3.884)	(4.200)	(3.880)	(6.119)	(3.659)
Constant	2.096***	2.541***	3.220***	4.302***	3.054***	2.865***	1.602***	2.429***
	(8.316)	(15.969)	(17.827)	(15.790)	(12.595)	(15.990)	(3.526)	(11.163)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Clustered Errors	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,980	10,995	10,966	11,008	10,959	11,016	6990	7116
R-squared	0.291	0.260	0.313	0.322	0.283	0.282	0.278	0.276

In this table, we examine the extent to which the quality of a firm's corporate governance and its information quality shape the effect of *DGS* on *TOBINSQ*. We use the shareholdings of institutional investors to proxy for the quality of corporate governance (columns 1–2). We use stock illiquidity measured by Roll's (1984) bid-ask spread (columns 3–4) and analyst coverage (columns 5–6) as proxies for firm information quality. In the last two columns (7–8) we use IPO Age. We use sample median to distinguish between firms with high and low indicators. Regression variables are presented in Table 2. In all our regression specifications, we control for industry and year fixed effects. *t*-stats are reported between parentheses. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

stakeholders gain clearer insights into a company's digital initiatives, fostering confidence and reducing uncertainty. In addition, increased transparency allows investors to better evaluate the strategic advantages and potential financial gains associated with digital transformation, leading to the assessment of a firm's digital initiatives and capabilities.

In a final test, we use the median of 'IPO age' (i.e. age of the firm since its IPO year) of our sample firms to distinguish Junior IPO firms (below sample median) from Senior IPO firms (above sample median) and report the results in the last two columns of Table 6. We observe that DGS loads positively and significantly only for young IPO firms. This is plausible because these firms often exhibit greater agility in adopting and integrating new technologies compared to older firms burdened with established legacy systems. In the early stages of their business life cycle, these firms can implement innovative solutions without incurring substantial operating costs associated with digital transformation. As such, the impact of digital technologies is more likely to align with the growth-oriented nature of these firms. Our evidence confirms this prediction, suggesting that investors associate digital initiatives in young IPO firms with digital savvy, perceiving them as drivers of higher growth potential and value creation.

4. Conclusion

Corporate digital transformation is usually associated with efficiencies in the firm processes, culture, and operational methods. These efficiencies may contribute to cost reduction, optimized resource use, and an enhanced ability to meet dynamic internal and external demands, leading to innovation-led value creation. Our study corroborates this by demonstrating a positive relationship between organizational capital and concurrent and future corporate value. However, we find that OC, information quality, firm governance, and IPO age significantly influence the valuation impact of corporate digital transformation. Future research in this domain is essential. For instance, exploring how OC mediates the relationship between corporate digital transformation and various corporate outcomes, especially in a cross-country setting, is a valuable next step. In our study, we caution not to interpret our fresh evidence in a causal sense. Future research may extend our work by identifying shocks that address the potential endogeneity bias. Additionally, while this study does not examine the influence of corporate leadership on the valuation effects of digital transformation, it is a promising avenue for subsequent investigations.

Author statement

Generative artificial intelligence usage: none.

CRediT authorship contribution statement

Mobina Zareie: Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Najah Attig:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Sadok El Ghoul:** Writing – review & editing, Supervision, Conceptualization. **Iraj Fooladi:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

Appendix: List of Keywords

Artificial intelligence	Data processing system	E-service	Open source
Artificial reality	Data science	Face recognition	Organizational capital
App	Data visualization	Fintech	Platform
3D print	Decentralized finance	Green computing	Quantum computing
5G	Deep learning	Heterogeneous data	Robotics
Augmented reality	DevOps	Hightech	Robots
Automation	Differential privacy	High-tech	Selfdriving car
Autonomous driving	Digital	Human cloud	Semantic search
Autonomous technology	Digital currency	Image recognition	Sentiment analysis
Big data	Digital marketing	Image understanding	Serverless computing
Biometric	Digital twin	Industry 4.0	Sharing economy
Biometrics	Digitalization	Influencer	Smart agriculture
Bitcoin	Digitally	In-memory computing	Smart content
Blockchain	Digitization	Intelligent systems	Smart contracts
Bots	Distributed computing	Internet	Smart devices
Business intelligence	Ebusiness	Internet of Things	Smart factory
Click-through rate	E-business	IoT	Smart healthcare
Cloud	Ecatalogue	Machine learning	Smart home
Cloud collaboration	E-catalog	Metaverse	Smart investment
Cloud computing	Ecommerce	Mobile internet	Smart transportation
Cognitive computing	E-commerce	Mobile payment	Smartphone
Converged infrastructure	Edge Computing	Natural language processing	Social media
Cryptocurrency	Elearning	Neural network	Software
Data analytics	E-learning	New economy	Speech recognition
Data architecture	Emobility	Newsfeed	Text mining
Data capturing	E-mobility	NFC payment	Unmanned
Data integration	E-procurement	NLP	Virtual reality
Data lake	Epublishing	Office automation	Voice recognition
Data mining	E-publishing	Online	Web 3.0
Data monetization	Eservice	Open banking	Web based

References

Attig, N., El Ghoul, S., 2018. Organization capital and the cost of equity financing in medium-sized manufacturing firms. Contemporary Accounting Res. 35, 1616–1644.
Baker, M., Stein, J., Wurgler, J., 2003. When does the market matter? Stock prices and the investment of equity-dependent firms. Quarterly J. Econ. 118, 969–1005.
Brammer, S., Millington, A., 2008. Does it pay to be different? An analysis of the relationship between corporate social and financial performance. Strateg. Manage J. 29 (12), 1325–1343. https://doi.org/10.1002/smj.714.
Chappell, H.W., Cheng, D.C., 1982. Expectations, Tobin's Q, and investment: a note. J. Finance 37, 231–236.
Chen, W., Srinivasan, S., 2023. Going digital: implications for firm value and performance. Rev. Account. Studies. https://doi.org/10.1007/s11142-023-09753-0.
Chen, Y., Xu, J., 2023. Digital transformation and firm cost stickiness: evidence from China. Financ. Res. Lett. 52, 103510 https://doi.org/10.1016/j.frl.2022.103510.
Chung, R.M., Firth, M., Kim, J.B., 2002. Institutional monitoring and opportunistic earnings management. J. Corporate Financ. 8, 29–48.
Cui, L., Wang, Y., 2023. Can corporate digital transformation alleviate financial distress? Financ. Res. Lett. 55 (B), 103983 https://doi.org/10.1016/j.frl.2023.103983. Part.
Cui, H., Zhou, X., Luo, Y., 2023. Digital transformation and bond credit spread. Financ. Res. Lett. 58 (C), 104553 https://doi.org/10.1016/j.frl.2023.104553. Part.
Cui, H., Dai, L., Zhang, Y., 2021. Organization capital and corporate innovation: evidence from China. Financ. Res. Lett. 43, 101956 https://doi.org/10.1016/j.frl.2021.101956.

Daud, S.N.M., Ahmad, A.H., Khalid, A., Azman-Saini, W.N.W., 2022. FinTech and financial stability: threat or opportunity? Financ. Res. Lett. 47 (B), 102667. Part.

Eisfeldt, A.L., Papanikolaou, D., 2013. Organization capital and the cross-section of expected returns. J. Finance 68, 1365–1406.

Fabac, R., 2022. Digital balanced scorecard system as a supporting strategy for digital transformation. Sustain. 14 (15), 9690. https://doi.org/10.3390/su14159690.

Guo, X., Li, M., Wang, Y., Mardani, A., 2023. Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. J. Bus. Res. 163, 113868. ISSN 0148-2963.

Hartzell, J.C., Starks, L.T., 2003. Institutional investors and executive compensation. J. Finance 58, 2351–2374.

Huang, H., Wang, C., Wang, L., Yarovaya, L., 2023. Corporate digital transformation and idiosyncratic risk: based on corporate governance perspective. Emerg. Markets Rev. 56, 101045 https://doi.org/10.1016/j.ememar.2023.101045.

KPMG. 2023. KPMG global tech report: secure value by navigating uncertainty with confidence. Retrieved on December 24, 2023 from: https://kpmg.com/xx/en/home/insights/2023/09/kpmg-global-tech-report-2023.html?cid=ggl-cpc_ggl_all_xx_2023_kpmg-glb-tech_ad1&s_kwcid=AL!13704!3!682989594674!p!!g!!digital%20transformation&gclid=CjwKCAiAyp-sBhBSEiwAWWzTnsZpTZKUEG_QkxThlHsrN0gw6XKX6el7EBC4kj0ue9Dx48qwC4XVMxoCEwIQAvD_BwE.

Lev, B., Radhakrishnan, S., 2005. The valuation of organization capital. In: Corrado, C., Haltiwanger, J., Sichel, D. (Eds.), Measuring Capital in the New Economy. National Bureau of Economic Research and University of Chicago Press, Chicago, pp. 73–110.

Lev, B., Radhakrishnan, S., Zhang, W., 2009. Organization capital. Abacus 45 (3), 275–298.

Li, C., Huo, P., Wang, Z., Zhang, W., Liang, F., Mardani, A., 2023a. Digitalization generates equality? Enterprises' digital transformation, financing constraints, and labor share in China. J. Bus. Res. 163, 113924 https://doi.org/10.1016/j.jbusres.2023.113924.

Li, S., Yang, Z., Tian, &.Y., 2023b. Digital transformation and corporate performance: evidence from China. China Economic. J. 16 (3), 312–334.

Li, D., Pan, L, 2022. Digital transformation and slack resource reconstruction: how companies promote innovation in digital era. In: Xu, J., Altiparmak, F., Hassan, M.H.A., García Márquez, F.P., Hajiyev, A. (Eds.), Proceedings of the Sixteenth International Conference on Management Science and Engineering Management – Volume 1. ICMSEM 2022. Lecture Notes on Data Engineering and Communications Technologies, 144. Springer, Cham. https://doi.org/10.1007/978-3-031-10388-9_55.

Liu, G., Liu, B., 2023. How digital technology improves the high-quality development of enterprises and capital markets: a liquidity perspective. Financ. Res. Lett. 53, 103683.

Lu, Z., Lin, Y., Li, Y., 2023. Does corporate engagement in digital transformation influence greenwashing? Evidence from China. Financ. Res. Lett. 58 (D), 104558 https://doi.org/10.1016/j.frl.2023.104558. Part.

McLean, R.D., Zhang, T., Zhao, M., 2012. Why does the law matter? Investor protection and its effects on investment, finance, and growth. J. Finance 67, 313–350.

Marx, C., Haskamp, T., Uebernickel, F., 2023. Designing innovation in the digital age: how to maneuver around digital transformation traps. In: Meinel, C., Leifer, L. (Eds.), Design Thinking Research. Understanding Innovation. Springer, Cham. https://doi.org/10.1007/978-3-031-36103-6_15.

McKinsey & Co. 2019. Why do most transformations fail? A conversation with Harry Robinson. Retrieved on December 23, 2023 from https://www.mckinsey.com/capabilities/transformation/our-insights/why-do-most-transformations-fail-a-conversation-with-harry-robinson#/.

Panta, H., Panta, A., 2023. Organizational capital and readability of financial reports. Financ. Res. Lett. 55 (Part A), 103895.

Pedersen, C.L., 2022. Cracking the culture code for successful digital transformation. MIT. Sloan. Manage Rev. 63 (3), 1–4. https://ezproxy.library.dal.ca/login?url=https://www.proquest.com/scholarly-journals/cracking-culture-code-successful-digital/docview/2670468946/se-2.

PWC. 2017. 20 years inside the mind of the CEO... What's next? Report available at: https://www.pwc.com/gx/en/ceo-survey/2017/pwc-ceo-20th-survey-report-2017.pdf.

Rauh, J., 2006. Investment and financing constraints: evidence from the funding of corporate pension plans. J. Finance 61, 33–71.

Rogers, B., 2016. Why 84% of Companies Fail At Digital Transformation. Dec. 23.. Forbes. Retrieved on December 23, 2023 from. https://www.forbes.com/sites/brucerogers/2016/01/07/why-84-of-companies-fail-at-digital-transformation/?sh=701d51d3397b.

Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. J. Finance 39, 1127–1139.

Shleifer, A., Vishny, R.W., 1986. Large shareholders and corporate control. J. Political Econ. 94, 461–488.

Teng, X., Wu, Z., Yang, F., 2022. Impact of the digital transformation of small- and medium-sized listed companies on performance: based on a cost-benefit analysis framework. J. Math. 7, 1–14. https://doi.org/10.1155/2022/1504499.

Walsh, J.P., Ungson, G.R., 1991. Organizational memory. Acad. Manag. Rev. 16, 57–91.

Wu, K., Fu, Y., Kong, D., 2022. Does the digital transformation of enterprises affect stock price crash risk? Financ. Res. Lett. 48, 102888 https://doi.org/10.1016/j.frl.2022.102888.

Xu, G., Li, G., Sun, P., Peng, D., 2023. Inefficient investment and digital transformation: what is the role of financing constraints? Financ. Res. Lett. 51, 103429 https://doi.org/10.1016/j.frl.2022.103429.

Youndt, M.A., Subramaniam, M., Snell, S.A., 2004. Intellectual capital profiles: an examination of investments and returns. J. Manag. Studies 41, 335–361.

Zhang, Y., Ma, X., Pang, J., Xing, H., Wang, J., 2023. The impact of digital transformation of manufacturing on corporate performance – The mediating effect of business model innovation and the moderating effect of innovation capability. Res. Int. Bus. Finance 64, 101890. https://doi.org/10.1016/j.ribaf.2023.101890.

Zhang, W., Zhao, J., 2023. Digital transformation, environmental disclosure, and environmental performance: an examination based on listed companies in heavy-pollution industries in China. Int. Rev. Econ. Finance 87, 505–518.

Zhang, W., Liu, G., 2023. Digitalization and firm centralization: a quasi-natural experiment based on the "Broadband China" policy. Financ. Res. Lett. 52, 103495 https://doi.org/10.1016/j.frl.2022.103495.

Zhao, X., Cai, L., 2023. Digital transformation and corporate ESG: evidence from China. Financ. Res. Lett. 58 (A), 104310 https://doi.org/10.1016/j.frl.2023.104310. Part.

Zhong, X., Ren, G., 2023. Independent and joint effects of CSR and CSI on the effectiveness of digital transformation for transition economy firms. J. Bus. Res. 156, 113478 https://doi.org/10.1016/j.jbusres.2022.113478.