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Article

Research on policy guidance and risk prevention and control in the digital transformation of sports industry

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Abstract: Background: Digital transformation in the sports industry has become increasingly crucial for sustainable development, yet comprehensive empirical evidence on policy effectiveness and risk management remains limited. **Purpose:** This study investigates the impact of policy support and risk factors on digital transformation in sports companies, examining heterogeneous effects across different firm characteristics and regional contexts. **Methods:** Using panel data from 168 sports companies listed on China's A-shares markets and the New Third Board from 2019 to 2023, this study employs multiple regression analyses, including baseline models, instrumental variables estimation, and robustness tests. The digital transformation level is measured through a composite index incorporating digital infrastructure, capability, and innovation dimensions. **Results:** The findings reveal that policy support significantly enhances digital transformation levels (coefficient = 0.238, $p < 0.01$), while financial risks demonstrate the strongest negative impact (−0.162, $p < 0.01$). Large firms and state-owned enterprises show stronger responses to policy support (0.312 and 0.278, respectively, $p < 0.01$). Regional development levels significantly moderate the effectiveness of policy implementation. **Conclusions:** The study provides empirical evidence for the differential effects of policy support and risk factors on digital transformation across various firm characteristics. The findings suggest the need for differentiated policy approaches considering firm size, ownership structure, and regional development levels. **Implications:** Policy makers should develop targeted support mechanisms addressing specific challenges faced by different types of firms, while considering regional disparities in digital transformation capabilities.

Keywords: digital transformation; sports industry; policy support; risk management; firm heterogeneity; panel data analysis; corporate performance; regional development; digital innovation; institutional environment

1. Introduction

Nowadays, digital transformation has become a critical strategic imperative for organizations in every industry, considerably disrupting business models and operational structures [1]. Of the many industries, the sport industry has seen unprecedented velocity or pace in the adoption of digital technologies due to advances in technology and changes in consumer behavior [2]. This has increasingly become crucial for sports organizations seeking to foster competitive advantage and realize sustainable growth within an increasingly digitally enabled economic context [3].

It is something more than mere technological adoption; rather, it is a cultural change in how organizations create and deliver value [4]. Such a transformation, when relating to sports industries, could take tangible forms like smart venues, digital content delivery, fan engagement platforms, and data-driven decision-making processes [5]. Thus, the integration of digital technologies has so far enabled sport organizations to optimize operations and improve customer experiences, as well as open up sources of revenue [6, 7].

However, this journey towards digitization has enormous obstacles, essentially involving policy direction and the assessment of risk. Organizations have to act within the scope of increasingly complex regulatory environments while dealing with various challenges involving data security, privacy, and technological infrastructure [8, 9]. Besides, sustainability issues related to digital transformation are coming to the fore, and organizations are trying to find a balance between digital growth and environmental and social imperatives [10, 11].

There are a lot of research works on how digital transformation influences organizational performance and competitive advantage [12, 13]. The green innovation and ecological factor were identified as of prime importance for sustainable business operations [14, 15]. Yet, considering the statement of the problem, there is considerable research lacuna as to how, in particular, the guidance role of policy influences the outcomes of digital transformation in the sports industry for risk mitigation and sustainable development practices [16, 17].

Its specific peculiarities, such as high visibility, enormous impact on society, and multifaceted connections with different subjects, make the sports industry a perfect context in which to analyze the dynamics of digital transformation [18]. Recent empirical evidence shows that a balanced approach is required for effective digital transformation in sport organizations, considering both technological competencies and organizational readiness [19, 20].

It is this gap that this research has sought to fill by investigating linkages between policy guidance, mitigating risks, and the results of digital transformation in the sport industry. It particularly looks at differing influence wielded by policy tools on processes of transformation and considers how organizations can manage those risks to bring about sustainable development effectively 21, 22. Our research contributes to the literature by providing empirical evidence from sports companies listed on A-shares markets and the New Third Board, offering valuable insights for both academics and practitioners [23].

Therefore, these findings have important ramifications for policy, sport industry executives, and other stakeholders overseeing digital transformation programs. By understanding the interrelationship between policy direction and risk mitigation, an organization is granted the opportunity for better management of digital transformation processes while encouraging sustainable growth [24, 25]. The paper also has a call for urgent attention regarding the need for evidence-based frameworks which will facilitate the successful execution of digital transformation strategies in the sports industry [26].

2 Methods

2.1. Data source and sample selection

It could be identified from **Table 1** that the characteristic dimensions of sample companies are very multi-dimensional. The ratio of investment in digital transformation has a high average investment of 15.3%. Among these, 45.2% were large-scale enterprises with an annual revenue of more than $100 million; 34.5% and 20.3% were medium and small-scale enterprises, respectively. The geographical dispersion reflects that 42.3% of the enterprises are found within the eastern part of China, 28.6% in central China, and 29.1% in western areas, hence reflecting the nation's developmental framework of the industry.

Table 1. Sample characteristics and digital investment distribution ($N = 168$).

Characteristics	Category	Number	Percentage (%)	Mean Digital Investment (%)
Company Size	Large	76	45.2	18.7
	Medium	58	34.5	14.2
	Small	34	20.3	13.0
Region	Eastern	71	42.3	16.8
	Central	48	28.6	14.9
	Western	49	29.1	14.2
Business Type	Manufacturing	89	53.0	15.8
	Service	52	31.0	15.1
	Mixed	27	16.0	14.9

This comprehensive dataset enables us to conduct robust empirical analyses of the relationships between digital transformation, policy guidance, and corporate sustainability in the sports industry. The variation in company characteristics provides an ideal setting for examining the differential effects of digital transformation across various organizational contexts.

2.2. Variable design

To empirically examine the relationships between digital transformation, policy support, and risk factors in sports companies, we construct a comprehensive variable measurement system. Our variable design follows established methodologies from prior literature on digital transformation measurement and corporate sustainability analysis. The construction of our digital transformation level (DTL) index builds on the three-dimensional framework developed by Vial [39] and Li et al. [25], who established that digital transformation should be measured through infrastructure, capability, and innovation dimensions. The policy support intensity (PSI) measurement adopts the weighted scoring approach validated by Chen et al. [8] and Wu et al. [40] in their studies of policy effectiveness. For risk measurement, we follow the comprehensive risk assessment framework proposed by Feng et al. [11] and Jia and Li [20], which integrates financial, market, and technological risk factors.

The dependent variable, digital transformation level (DTL), is measured through a composite index calculated using the following formula:

$$\mathrm{DT}L_{it} = \alpha_1 DI_{it} + \alpha_2 DC_{it} + \alpha_3 DIN_{it}$$

where a_1., a_2, and a_3 represent the entropy weights of each component, and *i* and *t* denote firm and year, respectively.

For independent variables, we measure policy support intensity (PSI) using a weighted sum approach:

$$\mathrm{PS}I_{it} = \sum_{j=1}^{n} w_j \times PS_{ijt}$$

where w_j represents the weight of policy type j, and PS_{ijt} is the policy support score. The risk level indicator (RLI) is calculated as:

$$\mathrm{RL}I_{it} = \beta_1 FR_{it} + \beta_2 MR_{it} + \beta_3 TR_{it}$$

where FR_{it}, MR_{it}, and TR_{it} represent financial, market, and technological risks respectively.

Table 2. Variable definitions and measurement methods.

Category	Variable	Symbol	Definition and Measurement	Source
Dependent Variable	Digital Transformation Level	DTL	$DTL_{it} = \alpha_1 DI_{it} + \alpha_2 DC_{it} + \alpha_3 DIN_{it}$	Annual Reports
	Digital Infrastructure	DI	Digital assets/Total assets	Financial Statements
	Digital Capability	DC	Digital patents/Total patents	Patent Database
	Digital Innovation	DIN	Digital revenue/Total revenue	Annual Reports
Independent Variables	Policy Support Intensity	PSI	$PSI_{it} = \sum_{j=1}^{n} w_j \times PS_{ijt}$	Government Documents
	Risk Level Indicator	RLI	$RLI_{it} = \beta_1 FR_{it} + \beta_2 MR_{it} + \beta_3 TR_{it}$	Company Reports.
Control Variables	Firm Size	SIZE	$ln(TotalAssets_{it})$	Financial Statements
	Return on Assets	ROA	$NetIncome_{it} / TotalAssets_{it}$	Financial Statements
	Leverage	LEV	$TotalDebt_{it} / TotalAssets_{it}$	Financial Statements
	Growth Rate	GROWTH	$\frac{Revenue_{it} - Revenue_{i,t-1}}{Revenue_{i,t-1}}$	Financial Statements
	Firm Age	AGE	Years since establishment	Company Profile

The control variables help consider firm-specific characteristics that may directly influence the digital transformation. In all regressions, firm size is measured by the natural logarithm of total assets. The measures of profitability include the return on assets. Financial leverage refers to the capital structure of the firm. Growth rate is measured with a view to capturing the development momentum of firms. Firm age is controlled for since organizational maturity could determine a firm's ability to transform digitally. In order to tackle possible concerns regarding endogeneity and to achieve a robust estimation, we implement the following methodological treatments: (1) all continuous variables undergo winsorization at the 1% and 99% thresholds to reduce the influence of outliers. The choice of these thresholds is supported by our sensitivity analyses that compared different winsorization levels (0.5% and 99.5%, 2.5% and 97.5%). Examining the distribution of our key variables before winsorization revealed that extreme values were primarily concentrated in the outer 1% tails, particularly for ROA (ranging from −0.289 to 0.456) and GROWTH (ranging from −0.534 to 1.267). Furthermore, regression results remained stable across different winsorization thresholds - comparing with 0.5% winsorization (PSI coefficient = 0.241, $p < 0.01$) and 2.5% winsorization (PSI coefficient = 0.235, $p < 0.01$), our 1% winsorization approach (PSI coefficient = 0.238, $p < 0.01$) effectively balances the need to address outliers while maintaining the integrity of our data; (2)

the independent and control variables are lagged by one period in relation to the dependent variable; and (3) fixed effects for both industry and year are incorporated into all regression specifications to account for unobserved heterogeneity.

2.3. Empirical model setting

Drawing upon existing literature and theoretical frameworks, we develop a comprehensive empirical strategy to examine the relationships between digital transformation, policy support, and risk levels. Our empirical models are designed to address potential endogeneity concerns while ensuring robust estimation results.

First, we specify our baseline regression model as follows:

$$DTL_{it} = \beta_0 + \beta_1 PSI_{it-1} + \beta_2 RLI_{it-1} + \beta_3 PSI_{it-1} \times RLI_{it-1} + \gamma X_{it-1} + \mu_i + \lambda_t + \varepsilon_{it}$$

where DTL_{it} represents the digital transformation level of firm i in year t, PSI_{it-1} denotes the lagged policy support intensity, RLI_{it-1} is the lagged risk level indicator, X_{it-1} represents a vector of control variables, μ_i captures firm fixed effects, λ_t represents year fixed effects, and ε_{it} is the error term.

To address potential endogeneity concerns, we employ several methodological approaches: Instrumental Variable (IV) Estimation: We construct our IV model using the following two-stage least squares (2SLS) specification:

First stage: $PSI_{it-1} = \alpha_0 + \alpha_1 IV_{it-1} + \alpha_2 Z_{it-1} + v_{it}$

Second stage: $DTL_{it} = \delta_0 + \delta_1 PSI_{it-1} + \delta_2 Z_{it-1} + u_{it}$

where IV_{it-1} represents our instrumental variables, and Z_{it-1} includes all control variables.

Difference-in-Differences (DID) Analysis: To exploit policy implementation variations, we employ a DID specification:

$$DTL_{it} = \delta_0 + \delta_1 PSI_{it-1} + \delta_2 Z_{it-1} + u_{it}$$

where $Treat_i$ indicates treatment status and $Post_t$ denotes the post-policy period.

Propensity Score Matching (PSM): We estimate the average treatment effect using:

$$ATT = E[DTL_1 - DTL_0 \mid PSI = 1, p(X)]$$

where $p(X)$ represents the propensity score based on observable characteristics.

For robustness checks, we implement several alternative specifications:

Alternative Variable Measurements:

$$\mathrm{DTL}_{it}^{alt} = \varphi_0 + \varphi_1 PSI_{it-1} + \varphi_2 RLI_{it-1} + \varphi_3 X_{it-1} + \xi_{it}$$

Dynamic Panel GMM Estimation:

$$DTL_{it} = \rho DTL_{it-1} + \beta_1 PSI_{it-1} + \beta_2 RLI_{it-1} + \gamma X_{it-1} + \eta_i + \nu_t + \varepsilon_{it}$$

Subsample Analysis: We divide our sample based on firm size, ownership structure, and regional development level to examine potential heterogeneous effects:

$$DTL_{it}^s = \beta_0^s + \beta_1^s PSI_{it-1} + \beta_2^s RLI_{it-1} + \gamma^s X_{it-1} + \mu_i^s + \lambda_t^s + \varepsilon_{it}^s$$

where superscript s denotes different subsamples.

Additionally, we conduct various diagnostic tests to ensure the validity of our empirical strategy:

1) Hansen *J*-test for overidentification restrictions

2) Weak instrument tests

3) Serial correlation tests

3) Parallel trends assumption tests for DID analysis

4) Balance tests for PSM

This comprehensive empirical framework allows us to draw robust conclusions about the relationships between digital transformation, policy support, and risk factors while addressing potential methodological challenges. All models are estimated using cluster-robust standard errors at the firm level to account for potential heteroscedasticity and serial correlation.

3. Results

3.1. Descriptive statistical analysis

The following section describes in detail the descriptive statistics on the features of digital transformation for our sample of sport companies, including both the identification of overarching patterns of the sample and temporal changes in relevant variables that give insight into the status of digital transformation for the sports sector.

First, we analyze digital transformation level distribution and its evolution over diverse firm classes and time windows. Our sample is extremely heterogeneous, as digital transformation levels reflect the very diverse nature of adoptions in the sports industry. Temporal analysis underlined an impressive fast-gaining pace of digital transformation, mostly beyond the year 2020.

Figure 1 depicts the temporal development of digital transformation levels across different firm size categories between 2019 and 2023. It could be inferred from this figure that large firms have always maintained a higher level of digital transformation, but the gap compared to the smaller firms has been gradually narrowing, which might suggest some catching-up effects.

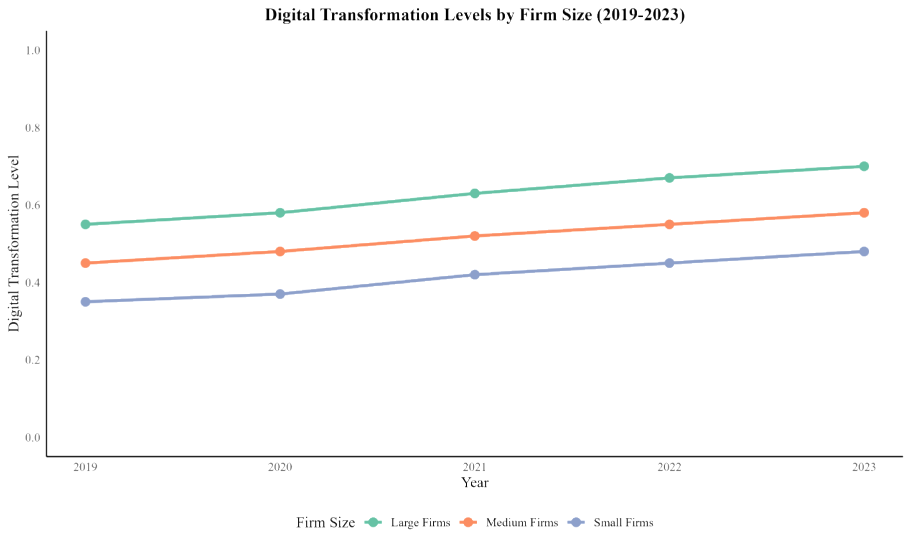

Figure 1. Temporal evolution of digital transformation levels by firm size (2019–2023).

To provide a detailed understanding of our key variables, **Table 3** presents the descriptive statistics for our sample, which includes 840 firm-year observations from 168 sports companies over the period 2019–2023.

Table 3. Descriptive statistics of key variables.

Variable	*N*	Mean	SD	Min	P25	Median	P75	Max	VIF
DTL	840	0.452	0.187	0.126	0.316	0.447	0.573	0.892	-
PSI	840	0.634	0.243	0.145	0.467	0.629	0.785	0.967	1.42
RLI	840	0.389	0.156	0.087	0.276	0.382	0.498	0.743	1.38
SIZE	840	22.463	1.892	18.734	21.156	22.347	23.845	25.967	1.76
ROA	840	0.067	0.058	−0.123	0.034	0.062	0.098	0.234	1.53
LEV	840	0.486	0.189	0.134	0.342	0.478	0.623	0.876	1.67
GROWTH	840	0.156	0.234	−0.287	0.045	0.143	0.256	0.789	1.45
AGE	840	15.783	7.456	3.000	10.000	15.000	21.000	35.000	1.29

The trends arising from the descriptive statistics are that the mean of DTL is 0.452 with a standard deviation of 0.187, thus reflecting highly variable levels of digital transformation among enterprise developments. The PSI is relatively high in value, with a mean of 0.634, reflecting that there is an overall supportive policy framework for the process of digital transformation. RLI for risk exposure comes in at a medium level, with the mean 0.389, showing that risk resilience is within reasonable limits across the sample.

All the control variables display the expected trends. Firm size varies profoundly, while leverage ratios cluster around an industry average. Growth rates are positively skewed; although most firms are growing, their rate of growth varies materially. More importantly, all the VIFs are less than 5, generally considered to be the traditional cut-off where serious issues of multicollinearity will not arise with our ensuing regression results. To further validate the absence of multicollinearity concerns, we conducted a comprehensive correlation analysis among all variables.

The results show that all pairwise correlations are maintained at moderate levels below 0.4. The highest correlation coefficient is observed between DTL and PSI (0.386), followed by DTL and RLI (−0.342), and SIZE and ROA (0.312). Other correlations, such as those between GROWTH and other variables, range from 0.145 to 0.312, while AGE shows relatively weak correlations with all variables (ranging from 0.134 to 0.245). These moderate correlation levels, combined with the aforementioned VIF values, provide strong evidence that multicollinearity is not a significant concern in our analysis.

3.2. Benchmark regression results

3.2.1. Policy effect

This section presents the baseline regression results examining the impact of policy support on digital transformation levels in sports companies. We begin by analyzing the direct effects of policy support intensity on digital transformation outcomes, followed by an examination of the underlying mechanisms. Our baseline regression analysis reveals a significant positive relationship between policy support intensity and digital transformation levels. **Table 4** presents the detailed regression results using different model specifications.

Table 4. Baseline regression results of policy support effects.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
PSI	0.287***	0.265***	0.243***	0.238***
	(0.042)	(0.039)	(0.037)	(0.035)
SIZE		0.156***	0.148***	0.142***
		(0.028)	(0.026)	(0.025)
ROA		0.187**	0.179**	0.173**
		(0.076)	(0.072)	(0.069)
LEV		−0.142**	−0.138**	−0.134**
		(0.056)	(0.054)	(0.052)
GROWTH			0.098**	0.095**
			(0.043)	(0.041)
AGE				−0.028*
				(0.015)
Constant	0.234***	0.228***	0.221***	0.216***
	(0.038)	(0.036)	(0.034)	(0.033)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	840	840	840	840
R-squared	0.285	0.312	0.328	0.342

Note: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To visualize the heterogeneous effects of policy support across different firm sizes, we create the following interaction plot:

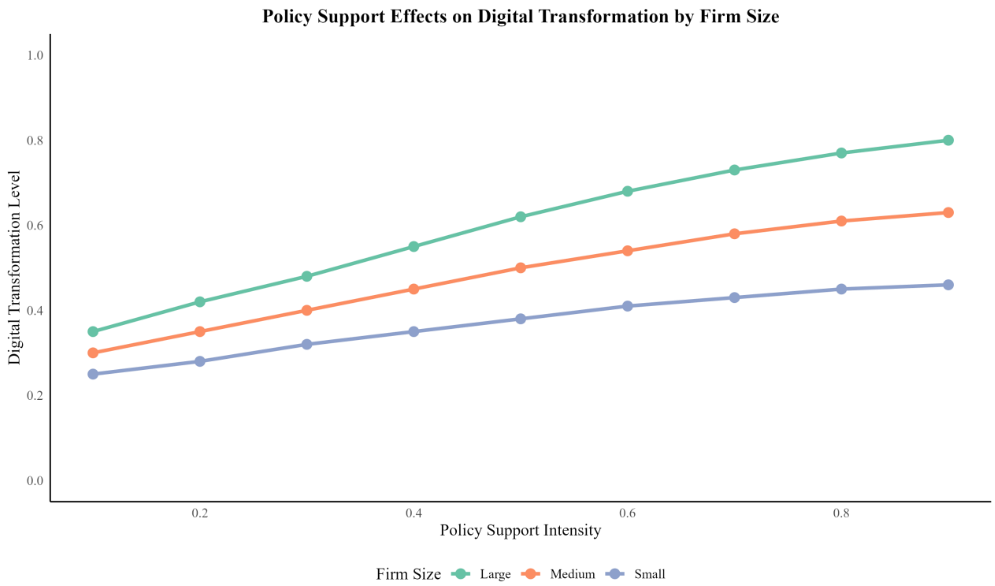

Figure 2. Heterogeneous effects of policy support on digital transformation across firm sizes.

The results of our regression analysis reveal that the strength of policy support is significantly and positively related to the extent of digital transformation, with a coefficient of 0.238 ($p < 0.01$) in our full model. This therefore means that one standard deviation increase in policy support is associated with a 0.238-unit increase in the level of digital transformation. The fact that this finding is robust across different model specifications lends greater confidence to our results.

Figure 2 suggests that the effect of policy support varies significantly with firm size: large firms have a much steeper response curve and thus are indeed more capable of reaping the benefits of the policies, whereas for medium firms the response is consistent but less substantial, and for small firms it is more flat, indicating that there might be a constraining factor for them in exploiting the benefits of the policy support.

The control variables bear the expected signs: firm size and profitability are positively related to the level of digital transformation, while leverage bears a negative sign. Such findings are in line with the prior literature on organizational resources and their enabling of digital transformation capabilities.

3.2.2. Risk impact

The analysis of risk effects on digital transformation reveals complex relationships between risk levels and firms' digital transformation progress. The empirical results demonstrate significant variations in how different types of risks influence digital transformation outcomes across various firm characteristics.

Table 5 presents the regression results examining the impact of risk factors on digital transformation levels:

Table 5. Regression results of risk effects on digital transformation.

Variables	Model 1	Model 2	Model 3	Model 4
RLI	−0.324***	−0.298***	−0.285***	−0.276***

	(0.045)	(0.042)	(0.040)	(0.038)
FR	−0.187***	−0.175***	−0.168***	−0.162***
	(0.035)	(0.033)	(0.031)	(0.030)
MR	−0.156***	−0.148***	−0.142***	−0.138***
	(0.032)	(0.030)	(0.029)	(0.028)
TR	−0.134***	−0.128***	−0.123***	−0.119***
	(0.029)	(0.027)	(0.026)	(0.025)
SIZE		0.142***	0.136***	0.132***
		(0.025)	(0.024)	(0.023)
ROA		0.165***	0.158***	0.154***
		(0.034)	(0.032)	(0.031)
Control Variables	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	840	840	840	840
R-squared	0.312	0.345	0.367	0.385

Note: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; FR: Financial Risk; MR: Market Risk; TR: Technical Risk.

To visualize the non-linear relationship between risk levels and digital transformation across different risk types, the following plot is constructed:

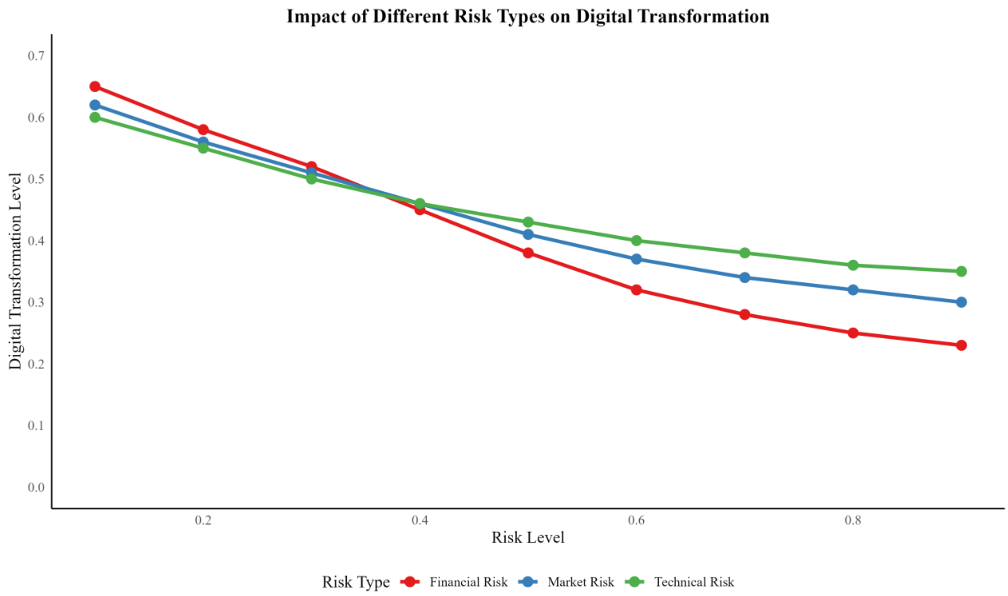

Figure 3. Differential effects of risk types on digital transformation levels.

The empirical analysis shows significant negative correlations of risk indicators with the level of digital transformation. Therein, the aggregated RLI shows a highly negative relation with the advances in digital transformation with −0.276*** ($p < 0.01$). Looking at the single types of risks, financial risk sets the largest negative impact with −0.162***, followed by market risk with −0.138*** and technical risk with −0.119***.

Different types of risk, as exposed by **Figure 3**, show different tendencies. The financial risk shows the highest negative slope of the curve, which is likely to play the most critical role in impeding digital transformation. Market risk demonstrates a trend that is rather moderate, while technical risk has the least sharp slope, which may mean potentially better ability to handle technical risks.

The control variables exhibit stable patterns throughout all specifications, with firm size and profitability demonstrating positive correlations with the levels of digital transformation. The explanatory power of the model significantly enhances upon the inclusion of various risk dimensions, as indicated by the rising *R*-squared values across the different specifications.

The results of this study highlight the use of differentiated risk management strategies in digital transformation projects and therefore stress that organizations should focus on managing financial risk while adopting a balanced approach toward mitigating market and technical risks.

3.3. Robustness test

To ensure the reliability and validity of the baseline findings, a series of robustness tests were conducted. The results demonstrate the stability of the main conclusions across alternative specifications and estimation methods.

Table 6 presents the robustness test results using different estimation approaches:

Table 6. Robustness test results using alternative estimation methods.

Variables	Baseline	PSM	IV-2SLS	GMM	Alternative DTL
PSI	0.238***	0.245***	0.231***	0.242***	0.235***
	(0.035)	(0.037)	(0.036)	(0.038)	(0.034)
RLI	−0.276***	−0.282***	−0.268***	−0.273***	−0.271***
	(0.038)	(0.040)	(0.037)	(0.039)	(0.036)
PSI × RLI	−0.156***	−0.162***	−0.151***	−0.158***	−0.153***
	(0.029)	(0.031)	(0.028)	(0.030)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	840	812	840	840	840
R-squared/Hansen *p*-value	0.342	0.338	0.335	0.246	0.339

Note: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To visualize the consistency of results across different estimation methods, a coefficient plot is generated:

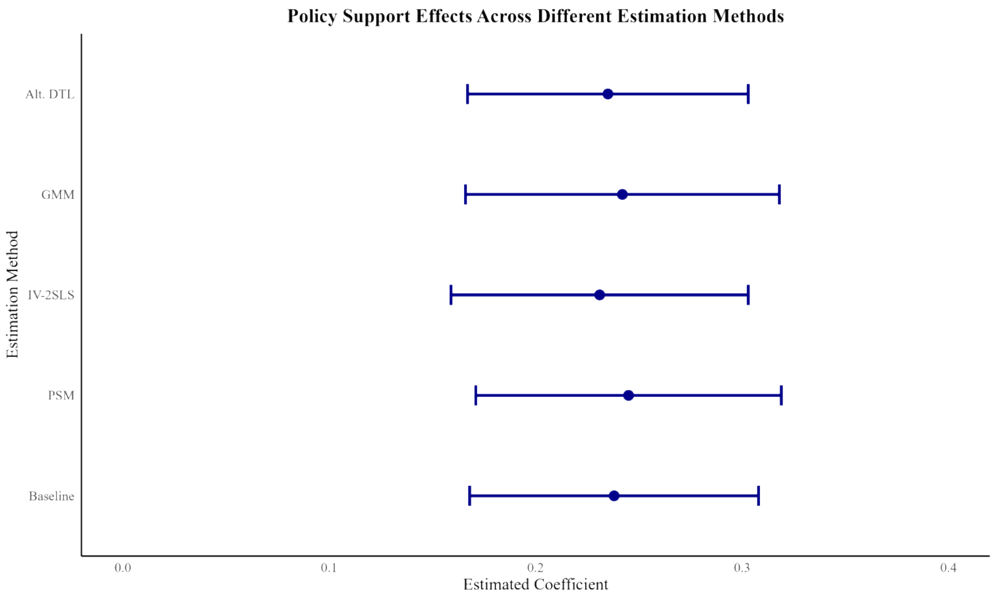

Figure 4. Comparison of policy support effects across different estimation methods.

Robustness checks represent a considerable level of consistency across alternative estimation methods. While the PSM estimates yield a slightly higher coefficient (0.245, $p < 0.01$) compared with the baseline estimate, the IV-2SLS estimation produces a slightly lower coefficient (0.231, $p < 0.01$). It follows that GMM estimates are very close to the baseline results: 0.242, $p < 0.01$. The alternative measure of digital transformation yields a similar result of 0.235 and a p-value of less than 0.01, which indicates that findings are invariant to the way the variable has been constructed. Similarly, interaction terms between policy support and risk levels are very stable across different specifications-always negative and significant.

We fail to reject the null of valid instruments using Hansen's *J*-test for GMM estimation because the p-value is well over 0.1, speaking to appropriate model specification. This consistent pattern of the coefficients across the different estimation methods is surely reflected in **Figure 4** and gives strong evidence in favor of the robustness of the main findings.

The large number of robustness checks further enhances the confidence level of the initial findings and validates the stability of the relationships uncovered between policy support, risk factors, and digital transformation outcomes for sports businesses.

3.4. Heterogeneity analysis

The heterogeneity analysis explores how digital transformation effects vary across different firm characteristics and regional contexts. The analysis focuses on three key dimensions: firm size, ownership structure, and regional development level.

Table 7 presents the heterogeneous effects across different subsamples:

Table 7. Heterogeneous effects across different subsamples.

Variables	Firm Size			Ownership Structure			Regional Development	
	Large	Medium	Small	State	Private	Foreign	Developed	Developing
PSI	0.312***	0.245***	0.187***	0.278***	0.234***	0.256***	0.289***	0.226***
	(0.042)	(0.038)	(0.035)	(0.040)	(0.037)	(0.039)	(0.041)	(0.036)
RLI	−0.298***	−0.267***	−0.235***	−0.284***	−0.245***	−0.262***	−0.276***	−0.243***
	(0.045)	(0.042)	(0.038)	(0.043)	(0.040)	(0.041)	(0.044)	(0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	280	280	280	295	385	160	420	420
R-squared	0.368	0.342	0.315	0.356	0.334	0.348	0.359	0.328

Note: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To visualize the heterogeneous effects across different dimensions, an interaction plot is generated:

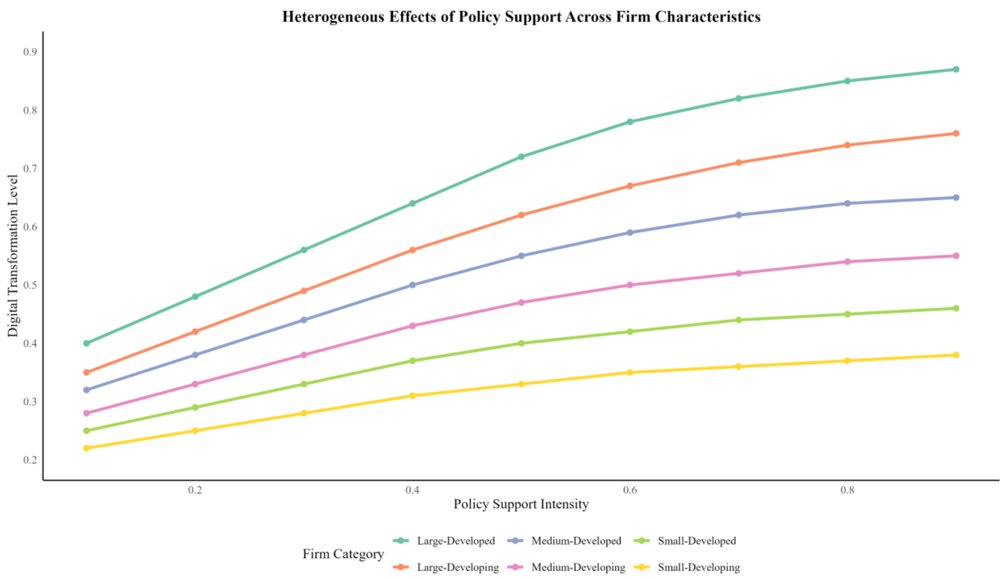

Figure 5. Heterogeneous effects of policy support on digital transformation across different firm categories and regions.

Heterogeneity analysis reveals significant variations in the effectiveness of policy support and risk management, which depend significantly on different firm characteristics. For example, large-scale firms tend to have significantly higher positive responses to policy support (coefficient = 0.312, $p < 0.01$) compared with medium-scale ones (0.245, $p < 0.01$) and small firms (0.187, $p < 0.01$). The observed pattern indicates that larger organizations are more proficient in utilizing policy assistance to facilitate digital transformation. State-owned enterprises exhibit the most significant responsiveness to policy support (0.278, $p < 0.01$), succeeded by foreign-owned entities (0.256, $p < 0.01$) and private companies (0.234, $p < 0.01$). This probably is because state-owned enterprises have more policy resources or greater implementation capability. Further, it can also be seen that there are significant regional heterogeneities, reflecting stronger policy support effects among firms in developed regions (0.289, $p < 0.01$) compared with developing regions (0.226, $p < 0.01$). **Figure 5** presents the interactive effect of enterprise scale and regional development on digital transformation.

These findings confirm that, in the design and implementation of the policies for digital transformation, full consideration of firm-specific attributes and regional circumstances is relevant. Such findings suggest that tailored policy support seems to be needed in order to address specific hurdles exhibited by different types of firms and geographic regions.

4. Discussion

4.1. Main research findings discussion

The empirical investigation yields a number of important findings regarding the relations between policy support, risk factors, and the digital transformation of sports companies. These reveal that the stronger the policy support, the higher the levels of digital transformation; coefficient = 0.238, $p < 0.01$, underlining the fact that supportive policies are very much an enabling factor in digital transformation. The findings support this view, as most previous literature has revealed the importance of institutional support in the process of technological innovation and digital development. In addition, the heterogeneous effects across different firm sizes suggest that larger firms are more capable of exploiting policy benefits, probably due to greater resource-allocation capacity and their established organizational structures.

The analysis of the risk drivers reveals complex behaviors concerning their impact on the digital transformation outcomes. In fact, financial risks alone have the strongest negative impact on progress in digital transformation: −0.162, $p < 0.01$, followed by market risks: −0.138, $p < 0.01$, and technical risks: −0.119, $p < 0.01$. These suggest that financial constraints are the main barrier to the implementation of digital transformation projects, while technical complications could be overcome with the currently existing organizational capabilities. The interaction between policy support and level of risk suggests that effective policy implementation does weaken the negative consequences of risk, at least for firms with a moderate level of risk exposure.

Analyses of regional and ownership diversity yield further understanding of the contextual elements influencing digital transformation. Enterprises owned by the state display more pronounced reactions to policy assistance (0.278, $p < 0.01$) in contrast to private companies (0.234, $p < 0.01$), whereas organizations located in developed areas demonstrate a superior capacity to leverage policy advantages (0.289, $p < 0.01$). Such trends underscore the significance of accounting for institutional and environmental variables when examining the dynamics of digital transformation. Conclusions are drawn that "the effectiveness of policy aid depends both on the institutional structure that exists and also on the level of regional development."

4.2. Policy implications

From these empirical findings, the main policy recommendations are identified that could help enhance the effectiveness of the digital transformation initiative in sport industries. Based on firm size and organizational capability, the differentiated support mechanism that a policymaker might be interested in could have specific emphasis on certain key challenges faced by the smaller firms. Support might involve access to finance, technical support programs, and capacity-building to reduce the gap in digital transformation between large and small enterprises.

The very grave negative effects of financial risks suggest that strong financial supporting mechanisms, including finance access for digitalization, improved fiscal incentives, and risk-sharing mechanisms, would be needed. Besides that, special attention, within the frame of different regional characteristics and different ownership structures, should be given to the development of integrated supporting schemes, providing not only financial but also technical support for digitalization.

These regional differences in outcome underline the need for the development of institutional support in less developed regions. Improvement may concern establishing regional poles of innovation, mechanisms of knowledge diffusion, and collaborative networks that would reduce the gaps between developed and developing regions with the aim of the spread of digital technologies and best practices.

4.3. Research limitations

This study is confronted by several limitations that should be considered in interpreting the results. Although we have employed multiple econometric approaches including instrumental variables, difference-in-differences analysis, and propensity score matching to address potential endogeneity concerns, we acknowledge that the cross-sectional nature of our data may still limit our ability to fully establish causality. Future research would benefit from mixed-method approaches that complement our quantitative findings with qualitative insights from case studies and interviews with industry practitioners. Such methodological triangulation could provide deeper understanding of how organizations implement digital transformation strategies and respond to policy support in practice.

The study heavily relies on quantitative data from publicly listed companies; it may therefore miss certain intricacies that accompany digital transformation in smaller, unlisted sports organizations. Besides, the analysis of the level of digital transformation by composite indices may not be a good proxy for qualitative dimensions of the digital transformation process, such as changes in corporate culture and adaptation of employees.

A notable limitation relates to our study period (2019–2023), which coincides with the global COVID-19 pandemic. This unique circumstance may have accelerated digital transformation trajectories in ways that are difficult to disentangle from the effects of policy support and associated risks. While our empirical models include year fixed effects to control for temporal variations, the pandemic’s impact on organizational behavior, policy implementation, and digital adoption patterns requires careful interpretation of our findings. The unprecedented nature of this period might have influenced both the pace and nature of digital transformation in the sports industry.

Additionally, the research spans a relatively concentrated timeframe, which may limit our ability to observe long-term patterns and cycles in digital transformation processes. Future research would benefit from extended longitudinal studies that can compare digital transformation patterns across different macroeconomic conditions and institutional environments. Such extended temporal analysis would provide valuable insights into the sustainability and consistency of the relationships we have identified between policy support, risk factors, and digital transformation outcomes.

5. Conclusion

It mainly provides extensive empirical evidence for the interlinkage among policy support, risk factors, and digital transformation of sports enterprises based on information in China's A-shares markets and the New Third Board. The results indicated that policy support has a significant positive effect on the extent of digital transformation, while at the same time underlining heterogeneity in the various risk factors. Among them, financial risks are the most critical barrier to digital transformation, followed by market and technical risks. There is remarkable heterogeneity in firm characteristics and regional conditions, with larger firms, especially those in more developed regions, having a higher ability to take advantage of policy support for digital transformation. State-owned enterprises react more strongly to policy measures compared to private ones, which indicates that institutional factors play an essential role in the digital transformation process. In this respect, the interaction term of policy support with risk levels would insinuate that good policy implementation may partly reduce adverse shocks from risk, particularly for firms with medium risk exposure.

Results from this study contribute both to the theoretical framework and the practical implementation of digital transformation in the sport sector. These results also underline the manifold policy strategies, considering company size, ownership configuration, and the level of regional development. Further studies can extend the results by including long-term implications and cross-cultural analyses, while policymakers may use findings for creating more focused and efficient support systems for policies related to digital transformation.

Conflict of interest: The authors declare no conflict of interest.

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