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Empirical Data from 2010-2020 and Evidence of Enterprise Management relationship with Digital Transformation and Big Data Technologies

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ABSTRACT

Digital transformations and big data technologies offer unique organisational development and innovation opportunities in modern business. The study aims to determine the complexities and challenges of using big data for organisational growth in the digital transformation process in enterprise management. An empirical study was conducted to analyse several factors to understand the influence of digital transformation initiatives on business operations. For 2010-2020, data was collected from the China stock market and accounting research database in Shanghai and Shenzhen states of China. Study findings show that by overcoming the challenges of big data technology, new and significant growth and innovation opportunities in business practices are possible and that big data should be used most effectively with strong data governance by developing talent, encouraging multidisciplinary collaboration, setting clear performance targets, and supporting algorithmic transparency. The study also stresses the need for a resilient, adaptive, and continually developing mindset to navigate the digital landscape effectively. Transformation of the enterprise's success required technical proficiency and commitment to ethical, responsible, and sustainable behaviour. The opportunities of big data technology and tackling its problems head-on. The organisations see themselves as industry leaders who lead innovation, competitiveness, and social value creation.

Keywords: Digital Transformation; Big Data Technology; Organizational Development; Data Governance; Innovation; China

1. INTRODUCTION

In today's fast-changing business environment, transformation is essential for businesses that want to stay relevant and competitive. A revolutionary tool that lets businesses use massive amounts of data to make strategic decisions and enhance operational efficiency, big data technology lies at the core of this transformation. Big data technology can extract valuable insights from various data sources, including operational processes and customer interactions. By applying advanced analytics and machine learning algorithms to find patterns, trends and connections within their data, businesses can use data to make confident decisions. In effect, digital transformation, powered by big data technology, brings a paradigm shift in business management, letting in creativity and agility while challenging long-held truisms (Azeroual & Fabre, 2021). This transformation includes embedding digital capabilities into every aspect of the business, from internal procedures to consumer interaction (Baig et al., 2021). By leveraging cloud computing, the IoT (Internet of Things), and other digital technologies, enterprises enable collaboration, accelerate processes, and provide consumers with individual experiences (Burgin & Mikkilineni, 2021).

Similarly, big data technology helps organisations better understand consumer behaviour and preferences. It allows them to develop personalised marketing campaigns and loyalty programs that fortify consumer attachment (Azeroual & Fabre, 2021). By examining vast quantities of structured and unstructured data from numerous sources (e.g., social media and online transactions), firms can tailor offerings and add-on services to closely match consumers' evolving needs. Thus, Dubey et al. (2020) showed that a customer-centric approach positively affects a firm's competitive advantage and brand reputation and helps shape long-lasting customer relationships. Enterprises alike may improve their operations and resource management with the help of big data technology and digital transformation. As real-time monitoring and predictive analytics with big data allow organisations to find inefficiencies, reduce risk, and take advantage of new cost-saving and revenue-generating opportunities, overall operational efficiency and streamlined processes, including manufacturing processes and supply chain management, are generated from significant data insights (Gao et al., 2023).

Big data analytics and digital transformation allow enterprises to react quickly and to adopt changes and growing trends in the market. Through the adoption of data-driven decision-making, organisations can granularly understand and anticipate market changes, find new growth opportunities, and outmanoeuvre the competition. Organisations can respond quickly to new trends, further iterate, test, and innovate, leveraging big data and digital transformation as the foundation of flexible and responsive business models (Gao, 2022; Shaikh et al., 2022). Similarly, big data is a key enabler when organisations embark on digital transformation and plays a crucial role in developing and implementing digital strategies within organisations. While implementing big data solutions may take away a massive chunk of the project budget, deciding not to involves even more significant risks because the fast pace, huge variety, and volume of data being processed not only push the edge of computing but also challenge our ability to make sense of it at the rapid pace at which it is being produced (Gil-Gomez et al., 2020).

There is a need to create a culture of learning and experimentation, breaking down organisational silos so that businesses have people who can communicate the requirements to the data scientists and quants that can return the results in a way that is usable by the business (Hassani et al., 2021). Organisational boundaries are not the only thing that has been and will continue to be disrupted by the digital transformation driven by big data. Industrial ecosystems and social dynamics can also be reconfigured by combining digital technology and big data. In this respect, a culture change from being led by data is necessary for digital projects to succeed. Technical skills are important, but a change in mindset towards data-driven thinking is also essential to break up data silos by making big data technologies available more broadly to employees (Gil-Gomez et al., 2020).

Burgin and Mikkilineni (2021) showed that big data and digital technology break down traditional industrial structures, enabling firms to form new partnerships and co-create value. Innovations can be driven across value chains when businesses share data-driven insights, form strategic partnerships, and co-create value with all those in their value chain. All supply chain stakeholders can readily access large, shared data stores stored in the cloud to drive real-time innovation and co-creation (Hautala-Kankaanpää, 2022). Finally, the digital transformation driven by big data technology can solve some of the most urgent global challenges and create economic growth. Specifically, by examining large datasets about urban development, environment sustainability, and healthcare, organisations can obtain immediate and valuable insights that can be used to guide policy decisions to act for a sounder social impact (Hautala-Kankaanpää, 2022).

Governments can also use data-driven insights to enhance public services and build infrastructure. In this way, healthcare providers can employ predictive analytics to improve patient outcomes and reduce healthcare costs (Bag et al., 2020). However, enterprises must navigate ethical, privacy and security concerns associated with big data technology and the benefits derived from digital transformation and noted that issues involving data privacy, consent, and ownership are rising along with the explosion of data. They must ensure they have robust data governance frameworks to protect individuals' rights and private data, stay on top of regulations such as the General Data Protection Regulation and comply with moral standards (Hautala-Kankaanpää, 2022). The rise of big data analytics also has led to growing concerns about algorithmic bias, discrimination, and unknown consequences. Ji et al. (2023) stated that machine learning algorithms are trained on biased datasets; they can take on and replicate systemic biases. Further perpetuating inequality is particularly troubling in criminal justice, lending, and employment decisions. Companies must prioritise transparency, accountability and equity to minimise bias entering algorithmic decision-making and ensure fair outcomes (Kostakis & Kargas, 2021).

Organisations leveraging big data technology for digital transformation must consider several challenges and devise solutions. Processing large volumes of diverse datasets is a top challenge that frequently leads to data silos that span various business units (Li, 2020). Integrating data sources ensures consistency and quality, crucial for informed decision-making and extracting relevant insights (Azeroual & Fabre, 2021). Organisations also contend with maintaining data security, and the rising cyber threats and the march of regulations make maintaining data security and privacy an uphill battle (Baig et al., 2021).

Robust cybersecurity processes and governance frameworks must be in place to protect sensitive data from unauthorised access, breaches and abuse and to comply with changing privacy mandates such as the general data protection regulation (GDPR) (Hassani et al., 2021). Another pressing issue is the lack of proficient staff to use extensive data technology and refined analytics competently (Ji et al., 2023). Organisations cannot fully tap extensive data because of a skills gap generated by an imbalance in the demand and supply for data scientists, analysts, and engineers (Ji et al., 2023)—the ethical obligations of extensive data analytics also concern enterprises and problems involve algorithmic bias, discrimination, and transparency (Kostakis & Kargas, 2021). Creating flexible, scalable architectures that support growing data volumes and many analytical workloads requires deliberate planning and investment in technology infrastructure (Gil-Gomez et al., 2020). Organisational inertia and cultural resistance can also slow the approval and execution of digital transformation projects inside businesses (Kostakis & Kargas, 2021).

The research structure integrates the transformative role of big data in enterprise management. It commences with an introduction to big data's influence on business, followed by a literature review analysing existing research on digital transformation and big data. It also focuses on digital transformation's impact on business aspects like resource allocation. Subsequently, the study delves into further research areas, highlighting industry-specific nuances with their practical implications for businesses and the overall impact on the business landscape.

2. LITERATURE REVIEW

Several studies have been conducted to discuss digital transformation and the adoption of big-data technologies in corporate sector management, including banking and other industries. However, this study aims to review the challenge of transformation of enterprise management. According to Liu et al. (2023), big data analytics offers solutions that make it possible to drive answers from the data.

It stated that technology can substantially enhance firms' ability to make high-quality data-driven decisions by allowing them to derive actionable insights from large data sets and incite innovation. Enterprises can leverage sophisticated analytics methods in machine learning and predictive modelling to unveil hidden patterns, trends, and correlations in their data, leading to more innovative and efficient decision-making processes.

Lutfi (2021) stated that technology enhances customer experiences and helps drive customer-centric initiatives. Additionally, it stated that big data analytics helps in gaining a comprehensive understanding of customer behaviour, preferences and emotional states; through the analysis of numerous data sources, namely social media interactions, online transactions and customer feedback, firms can personalise goods and services, improve marketing campaigns and enhance overall customer satisfaction and loyalty (Lutfi et al., 2022). Mangla et al. (2021) and Mikalef et al. (2020) examine the impact of big data analytics on improving supply chain management efficiency, refining the manufacturing process and enhancing inventory management. Real-time monitoring and predictive analytics tools enable organisations to rapidly detect inefficiencies, handle risks and exploit opportunities to reduce costs and increase revenue.

Munawar et al. (2020) underscore the significance of corporate culture, leadership, and people management in successful digital transformation endeavours. Digital transformation is not a technology project but about unlocking culture to change. Successful leadership, setting a vision and managing change are critical for overcoming resistance, breaking down silos between different divisions and propagating cultural transformation (Nasrollahi et al., 2021). However, besides the potential benefits of big data technology, scholars highlight other challenges and concerns organisations must address, such as the fundamental challenge of managing and integrating vast, diverse data sets from various sources. The complexities associated with data integration, data cleansing and governance will likely stymie organisations' ability to extract meaningful insights from their data (Qi et al., 2023; Makhdoom et al., 2023). Figure 1 shows the network of technology used in management.

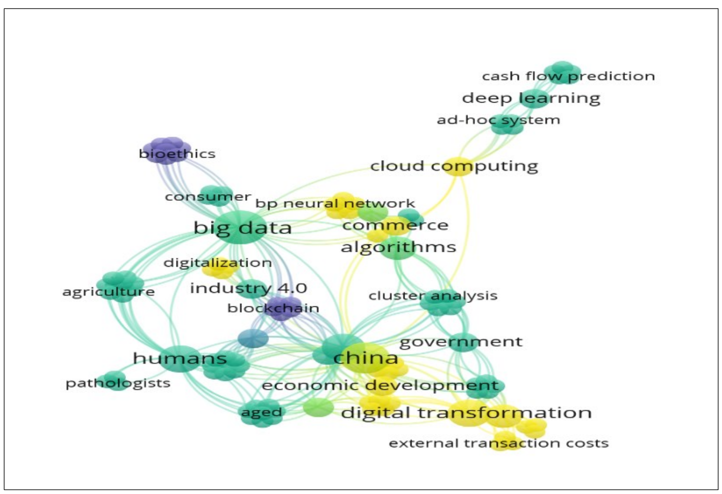

Figure 1. Keywords Co-occurrence Network

Moreover, Sestino et al. (2020) underline the overwhelming significance of data privacy, security, and ethical issues in the age of big data. The potential risks associated with data breaches, hacking, and unauthorised use of private information occur when data is scooped and analysed significantly. Thus, organisations must implement robust data privacy measures.

Adhering to protocols such as general data protection regulations (GDPR) and interacting with people and firms based on ethical standards will maintain privacy and preserve the rights of individuals (Shen & Yuan, 2020). Meanwhile, Nasrollahi et al. (2021) and Lutfi (2021) expressed concerns about the potential for algorithmic bias and discrimination in big data analytics, with the algorithms that work on biased datasets can perpetuate discrimination and reinforce systemic biases in decision-making processes, fairness, accountability, and transparency are paramount when making algorithmic decisions to build trust and mitigate against the potential for unforeseen adverse consequences.

Shen and Yuan (2020) underline the absence of digital technology and data-driven, technique-savvy experts who can put recent advances in big data analytics and their capabilities—to full operational use. Organisations must recruit, train, and build a cadre of data-proficient workforces that can not only Spirit innovation but collaborate and enhance it across value chains by putting data to work to realise a competitive edge. (Azeroual & Fabre, 2021). Tang and Yang (2023) investigated the implications of digital technology and data-driven methods in blurring traditional organisational boundaries and fostering new possibilities for cooperation and innovation. Organisations use data-driven analysis to set strategic alliances, collaboratively engender value with partners through their ecosystem, and stimulate collaborative innovation across their value chains (Baig et al., 2021).

In addition, there is ample evidence of the potential of big data analytics to be employed as a way to foster socioeconomic development and tackle critical global challenges. Thus, Gao et al. (2023) explored that data-driven methods could underpin evidence-based policy, enhance the provision of public services and give rise to positive social outcomes. Vial (2021) underscored the importance of cross-disciplinary collaboration and stakeholder involvement in complex, significant data technology matters and highlighted the need for collaboration among business, academia, Government, and civil society to advance responsible innovation and shape the course of digital transformation. Thus, through engagement in open dialogue, information sharing, and joint problem-solving, stakeholders can collaboratively address issues such as data governance, safeguarding privacy, and value-sensitive design (Wahab et al., 2021).

Moreover, Wen et al. (2021) explored the role of regulatory frameworks and policy interventions in overseeing big data technology's ethical and socially conscious employment. They suggested that governments must balance fostering innovation and protecting individual and collective rights and interests. In this way, the general data protection regulation aims to improve data security, facilitate transparency, and give individuals greater control over personal information; it also showed that ongoing learning, adaptation and perseverance are critical to successfully navigating the nuances of digital transformation and the big Data technology that drives it. Additionally, Yang et al. (2018) further explored the concept of digital transformation. Organizations must evolve and adapt to survive and flourish in the digital. It is through a culture of trial and error, adaptability, and continuous improvement that businesses can lay the groundwork today for their sustained agility amid the chaos of technology-driven disruption and market unpredictability tomorrow.

Significant progress has been made in deploying big data technology for digital transformation, but many gaps and challenges still must be addressed. Thus, Liu et al. (2023) addressed the more significant gaps in more holistic frameworks and procedures for data governance and management. Despite recognising the urgent need for data governance to ensure data quality, integrity, and compliance, many companies struggle to establish comprehensive governance frameworks encompassing all facets of data management, including collection, storage, analysis, and distribution another gap in talent development and skill acquisition. Despite the mounting demand for data scientists, analysts, and other data-related positions, there is still a dearth of quantitatively literate professionals proficient in using big data technology and advanced analytics methodologies. In response, savings are initiated to support talent development programs, training initiatives, and academic partnerships to build a capable and diverse workforce steeped in using big data technology to drive digital transformation. Despite allocating substantial resources to digital transformation initiatives, many businesses have challenges evaluating the return on investment and quantifying the advantages. In this regard, establishing uniform measurements and assessment structures may assist businesses in monitoring advancements. These pinpointing areas need enhancement, and the significance of digital transformation endeavours needs to be showcased to stakeholders.

3. METHODOLOGY

3.1. Data Source

This study uses a panel of publicly traded companies in the Shanghai and Shenzhen markets from 2010 to 2020 as the original study sample. The data is then processed in the following manner: Initially, we eliminate banking establishments, which include entities involved in real estate activities. The year of the economic recession in 2008 and COVID-19 in 2020 were excluded. The firm's economic statistics are sourced from the China Stock Market and Accounting Research Database (CSMAR). The overall information is sourced from the National Bureau of Statistics.

3.2. Variables

Richardson (2006) proposed that a firm optimal model was used to determine the firm's current capital spending and fundamental variables. Through regression analysis, we calculate the total amount of the residual term to evaluate the effectiveness of investments. The regression model is shown in Equation 1

$$\begin{aligned} \mathrm{INV}_{i,t} = \delta_0 + \delta_1 \mathrm{RGD}_{i,t-1} + \delta_2 \mathrm{LEV}_{i,t-1} + \delta_3 \mathrm{Cash}_{i,t-1} + \delta_4 \mathrm{DA}_{t-1} + \delta_5 \mathrm{AD}_{i,t-1} + \delta_6 \mathrm{Retu} \\ + \delta_7 \mathrm{INV}_{i,t-1} + \sum \mathrm{Industry} + \sum \mathrm{Year} + \varepsilon_{i,t} \end{aligned} \quad (1)$$

Equation 1 is based on Thchardson's (2006) investment model to forecast the predicted spending on investment in new positive NPV projects $INV_{i,t}$, representing the ideal amount of expenditure. It is determined mainly by actual variables: net company expenditure on net intangibles, fixed property, and other resources at the end of the year.

$RGD_{i,t-1}$ represents the company's digital revenue growth, which is calculated based on the rate at which its operational income increases.

$LEV_{i,t-1}$ represents the ratio of leverage.

$Cash_{i,t-1}$ represents the proportion of cash and its substitutes about the total value of properties.

$DA_{i,t-1}$ represents the years the listing uses the logarithmic function.

$A_{di\ t-1}$ represents the square root of the total resources using the logarithmic function.

$Return_{s,t-1}$ represents the yearly return for all stocks, considering the return of cash dividends.

Each variable is handled with a latency of one period. The variables "Industry" and "Year" represent fixed impacts for the sector and time, respectively. The residual term, denoted as $\varepsilon_{i,t}$, captures the inefficiency of business investment that has to be estimated by the model. A greater magnitude of residuals suggests a greater level of unproductive expenditure. Furthermore, when the actual value of the term residual (prior to the total calculation) exceeds zero, big data (BDU) is used. Conversely, when the residual value is below zero, it leads to a Digital return on investment (DROI). Figure 2 shows the research flowchart.

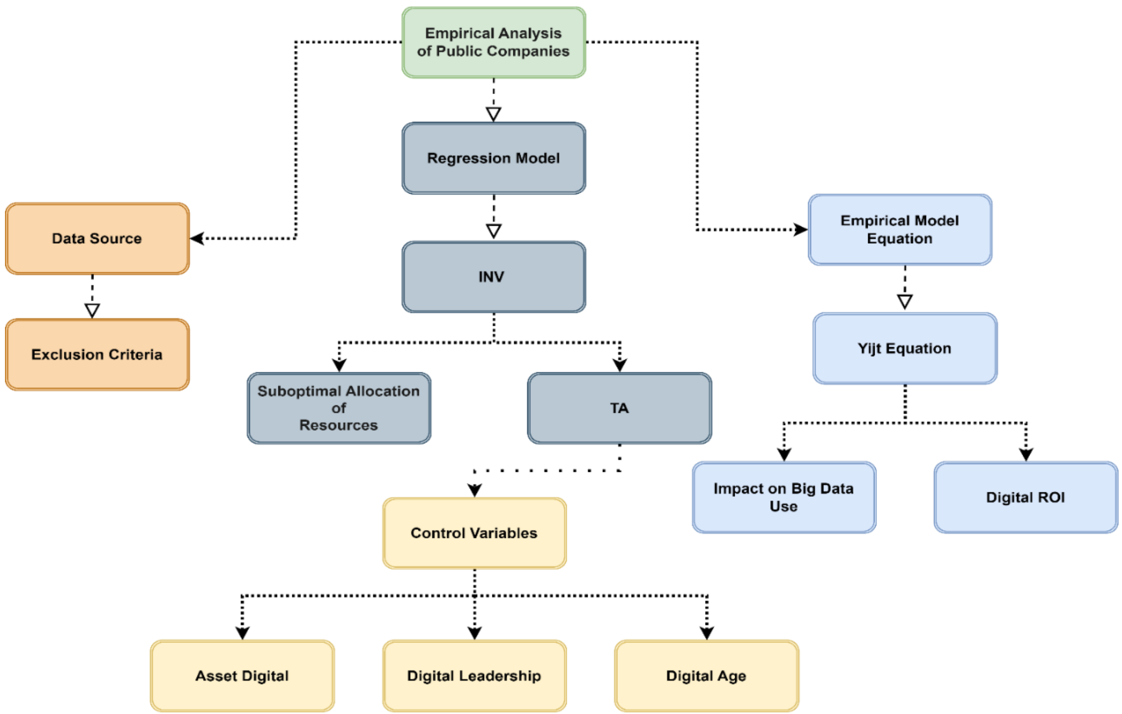

Figure 2. Research Method Flowchart

Literature studies suggested that evaluating digital transformation in businesses is typically subjective. However, suppose a binary substitute parameter is used to measure digital transformation (DT). In that case, it is suggested that DT is a tactical choice for achieving equitable growth and has a considerable temporal persistence. Thus, Wu et al. (2021) and Ren and Li (2022) used Python-based technologies and text methods to get the yearly filings of all publicly traded companies. The company's DT index is created by developing a vocabulary connected to DT and analysing text. A higher frequency of associated terms suggests a stronger inclination towards DT among organisations. It used a logarithmic modification to the word count associated with DT to address right-skewness—control variables (CVs). Concerning current research, we choose CVs, including asset digital (AD), digital leadership (DL), digital efficiency (DE), revenue growth digital (RGD), debt digital (DD), leadership structure (LS), and digital age (DA).

3.3. Empirical Model

According to the research by Benlemlih and Bitar (2018), we derive the subsequent formula as shown in Equation 2

$$\mathrm{Y_{ijt}} = \alpha_0 + \alpha_1 \mathrm{TA_{ijt}} + \eta \mathrm{CVs_{ijt}} + \mathrm{firm_i} + \mathrm{indu_j} + \mathrm{year_t} + \varepsilon_{\mathrm{ijt}} \tag{2}$$

Where i, j and t represent the company, industry, and year indices.

Y represents BDU (Big Data Utilization)

TA refers to Tech Adoption,

CVs refer to Control Variables.

ε represents a stochastic or unpredictable deviation from the actual value. In order to mitigate the influence of variations across firms on the empirical findings, we use industry, individual and period dummy factors.

4. RESULTS AND ANALYSIS

4.1. Analyses of Multicollinearity and Summary Data

Table 1 describes the statistical measures of panel A and presents that considerable data utilisation (BDU) consists of 52,564 observations, with an average mean value of 6.2244 and a standard deviation of 7.71855. Similarly, the dataset digital return on investment (DROI) has 65,054 observations, with a mean value of 3.65 and a standard deviation of 3.08595. These statistics provide information on the average and spread of each variable in the dataset.

Variance inflation factors (VIF) are used in Panel B to perform a multicollinearity study and evaluate the degree of multicollinearity among the variables, such as teach adoption (TA), assets digital (AD), digital leadership (DL), Digital Efficiency (DE), revenue growth digital (RGD), digital debt (DD), leadership structure (LS) and digital age (DA) have VIF(Over) values ranging from 1.0815 to 1.7115, indicating low to moderate degrees of multicollinearity. It is worth mentioning that none of the variables show significant multicollinearity, as shown by VIF values that do not often surpass 10. Therefore, there is no need to take remedial measures such as removing highly linked variables or using regularisation methods in regression modelling.

Table 1. Analyses of Multicollinearity and Summary Data

Panel A	**Summary statistics**		
Variable	**Observations**	**Mean**	**SD**
BDU	52,564	6.2244	7.71855
DROI	65,054	3.65	3.08595
TA	10,761	3.0534	1.3272
AD	10,761	23.5305	1.2579
DL	10,761	0.2058	0.2877
DE	10,761	0.04515	0.05145
RGD	10,761	0.2562	0.57855
DD	10,761	-0.0126	0.1491
LS	10,761	0.2898	0.46935
DA	10,761	11.97	6.64965
Panel B	**Multicollinearity analysis**		
Variable	**VIF(Over)**		**VIF(Under)**

TA	1.092	1.092
AD	1.3965	1.3125
DL	1.512	1.4805
DE	1.113	1.1025
RGD	1.0815	1.0815
DD	1.0815	1.0815
LS	1.134	1.113
DA	1.7115	1.554

4.2. Benchmark Regression

Table 2 shows the regression results that Technology Adoption (TA) negatively impacts Digital Return on Investment (DROI) (-0.0945***) and Business Digital Utilization (BDU) (-0.0084***), suggesting that while digitalisation is crucial, its financial returns may not be immediate. The Revenue Growth Digitalization (RGD) significantly enhances both DROI (0.93975*) and BDU (0.03255*), representing substantial financial benefits. Debt Digitalisation (DD) negatively affects the DROI (-1.26315*) but increases BDU (0.1743*), indicating potential overleveraging. Asset Digitalisation (AD) positively affects BDU (0.0084*) but lowers DROI (-0.30555*), suggesting inefficiencies in asset deployment. Digital Efficiency (DE) negatively influences BDU (-0.1689), while Digital Age (DA) significantly reduces both DROI (-0.05985*) and BDU (-0.0021***), implying older digital frameworks hinder performance. Leadership variables (DL, LS) remain insignificant. F-statistics' significance supports model validity, though R^2 values are relatively low (0.03255–0.13545), indicating additional factors influence outcomes. Firms should optimise digital investments by aligning technology adoption with revenue growth and efficiency while managing debt-driven digitalisation.

Table 2. Benchmark Regression

	-1 DROI	**-2** DROI	**-3** BDU	**-4** BDU
TA	-0.0945***	-0.0735**	-0.00525	-0.0084***
	-0.0336	-0.03465	-0.00315	-0.00315
AD	-0.30555***		0.0084***	
	-0.0378		-0.00315	
DL	-0.14175		0.00945	
	-0.16065		-0.0126	
DE	0.34335		-0.1689**	
	-0.74655		-0.0756	
RGD	0.93975***		0.03255***	
	-0.0672		-0.00525	
DD	-1.26315***		0.1743***	
	-0.26775		-0.0231	
LS	0.0021		0.0063	
	-0.105		-0.0063	
DA	-0.05985***		-0.0021***	
	-0.00735		-0.00105	
_cons	3.9375***	10.987***	0.08085***	-0.07875
	-0.10815	-0.8421	-0.0084	-0.07035
YEAR	✓	✓	✓	✓
INDUSTRY	✓	✓	✓	✓
INDIVIDUAL	✓	✓	✓	✓
F	8.547	58.6425	3.3705	17.472

R2	0.07245	0.13545	0.03255	0.06195
N	6830.25	6830.25	4468.8	4468.8

Notes: *, **, and *** represent statistically significant thresholds of 10%, 5%, and 1%, respectively. The symbol √ indicates that fixed-effects or CVs are included, whereas the symbol × indicates that they are not.

4.3. Robustness Test

The benchmark analysis demonstrates an essential and adverse correlation between DT and inefficient expenditure but does not establish a causal link between them. Furthermore, because of the bias in selecting CVs and the variability of the independent factor DT at the individual company level, additional robustness tests are necessary to verify the reliability, efficacy, and coherence of the benchmark regress estimators.

4.3.1. Substituting The Data of The Dependent Factor

The Richardson (2006) model posits no occurrence of consistent excessive investment or not investing in publicly traded corporations' financial capital allocation policy. Failure to do so will result in systematic bias when employing the residual model to assess excessive investment and lack of investment. In the research conducted by Li and Zhang (2019), we substituted the expansion rate of operating revenue with Tobin's Q in the Development variable. Additionally, we have reevaluated the INV metric to examine our findings' strength and reliability.

$$\mathrm{INV}_{i,t} = (\Delta \mathrm{FI}_{i,t} + \Delta \mathrm{CIP}_{i,t} + \Delta \mathrm{PM}_{i,t} + \Delta \mathrm{IA}_{t} + \Delta \mathrm{DE}_{i,t} + \Delta \mathrm{GW}_{i,t}) - (\mathrm{DEP}_{i,t} + \mathrm{AMO}_{i,t}) \quad (3)$$

FI represents fixed impacts,

CIP represents construction in progress,

PM designates project materials,

IA represents intangible assets,

DE represents development expenditure,

GW shows goodwill, and

DEP and AMO represent depreciation and amortisation.

4.3.2. Substituting The Value of the Separate Factor

Table 3 summarises the robustness results obtained from six different regression models (-1 to -6) investigating the association between inefficiency and factors such as TA and DT. Specification -1 reveals that the TA exhibits a statistically significant negative coefficient of -0.0042, with a standard error of 0.00105, in the context of the inefficiency scenario. In specification -2, the variable DT has a significant negative coefficient of -0.0021, with a standard error of 0.00105. When considering specification -3, the relevance of TA is maintained with a coefficient of -0.0105 and a standard error of 0.00315 in the inefficiency scenario. Specification -4 highlights the persistent significance of DT in terms of underestimated inefficiency and extra controls, with a coefficient of -0.02835 and a standard error of 0.0084.

Specification -5 indicates the significance of DT in terms of inefficiency, with a coefficient of -0.00945 and a standard error of 0.00315; the same is followed in specification -6, with a coefficient of -0.06405 and a standard error of 0.0231. In addition, the analysis includes controls for specifications, such as year, individual, and industry variables. The F-statistics range from 17.8815 to 49.833, indicating the significance of the model. The R-squared values vary from 0.04095 to 0.1407, indicating the proportion of the variation in the dependent variable explained by the independent variables. The number of observations (N) varies from 4,195.8 to 10,601.85, indicating the sample size.

Table 3. Robustness Analysis

	-1	**-2**	**-3**	**-4**	**-5**	**-6**
	Inefficiency	**DROI**	**BDU**	**Inefficiency**	**DROI**	**BDU**
TA	-0.0042***	-0.0021***	-0.0105***			
	-0.00105	-0.00105	-0.00315			
DT				-0.02835***	-0.00945***	-0.06405***
				-0.0084	-0.00315	-0.0231
_cons	0.0441	0.03255***	-0.08295	0.04095	0.1638***	-0.0777
	-0.02877	-0.011445	-0.07077	-0.0294	-0.01155	-0.07245
Controls	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Individual	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
F	20.7165	49.833	17.8815	23.6775	31.479	18.852
R2	0.04095	0.1155	0.06405	0.04095	0.1407	0.0651
N	10,601.85	6130.95	4470.9	10,431.75	6232.8	4195.8

Notes: "*," "**," and "***" represent statistically significant thresholds of 10%, 5%, and 1%, respectively. The symbol √ indicates that fixed-effects or CVs are included, whereas the symbol × indicates that they are not.

4.3.3. Endogeneity Problem Test

Table 4 shows the findings of an endogeneity test performed inside a statistical analysis. The coefficients obtained from regression studies for each pair of variables being analysed are Total Assets (TA), Debt Ratio on Investment (DROI), Total Assets (TA) once again, and Book Debt to Equity (BDU). The coefficient of 0.98435 in the second column (-2) represents the link between the Instrumental Variable (IV) and DROI and is statistically significant at the 1% level. The third column (-3) displays the statistically significant coefficient (-0.0063) representing the link between TA and BDU. Finally, column four (-4) shows the coefficients for IV and BDU are -0.8358 and statistically significant.

Including controls such as year, industry, and individual aims to reduce the influence of any confounding variables. The F-statistic exhibits its maximum value in the first column (412.1675), indicating a robust overall model significance. The R-squared values range from 0.40215 to 0.65835 across multiple assumptions, indicating the percentage of variation the model explains. The sample sizes (N) for each regression analysis are presented, indicating the number of observations employed, which ranges from 4,468.8 to 11,299.05. The findings indicate meaningful connections between the studied variables, emphasising the need to include endogeneity in the statistical modelling process.

Table 4. Endogeneity Test

	-1	-2	-3	-4
	TA	**DROI**	**TA**	**BDU**
TA		-0.0021***		-0.0063**
		-0.00105		-0.00315
IV	0.98435***		0.8358***	
	-0.0147		-0.01575	
_cons	15.41085	11.6487***	-11.71695*	-143.83845***
	-10.3425	-0.79275	-7.0287	-16.88085
Controls	✓	✓	✓	✓
YEAR	✓	✓	✓	✓
INDUSTRY	✓	✓	✓	✓
INDIVIDUAL	✓	✓	✓	✓
F	412.1675	36.876	93.366	93.366
R2	0.40215	0.65835	0.4138	0.4138
N	11,299.05	6830.25	11,299.05	4468.8

Notes: "*," "**," and "***" represent statistically significant thresholds of 10%, 5%, and 1%, respectively. The symbol √ indicates that fixed-effects or CVs are included, whereas the symbol × indicates that they are not.

4.4 Discussion

The findings of this study align with the existing literature on digital transformation and big data analytics while offering new insights into their implications for business performance. The regression results reveal that technology adoption (TA) negatively impacts both Digital Return on Investment (DROI) and Business Digital Utilization (BDU), suggesting that while digital transformation is essential, its financial benefits may not be immediate, are supported by (Qi et al., 2023; Makhdoom et al., 2023), which underscore the strategic alignment's importance in optimising long-term benefits in digital investments.

The positive impact of revenue growth digitalisation (RGD) on DROI and BDU indicates that firms' successful leveraging of digital technology can enhance their revenue generation and realise substantial financial benefits. This finding is consistent with the literature, highlighting big data analytics' role in uncovering hidden patterns and driving data-driven decision-making for revenue optimisation (Liu et al., 2021; Khoso et al., 2024). Similarly, the positive influence of Debt Digitalization (DD) on BDU, despite its negative effect on DROI, suggests that while leveraging debt for digital initiatives increases digital utilisation, it may lead to financial inefficiencies. It aligns with concerns in the literature regarding the challenges of financial sustainability in digital transformation efforts (Sebastian et al., 2020).

The findings also highlight the role of asset digitalisation (AD) in digital transformation. While AD positively impacts BDU, it reduces DROI, indicating that inefficient asset allocation may hinder financial returns. It echoes the literature's emphasis on effective resource allocation and operational efficiency in digital transformation initiatives (Mangla et al., 2021). Additionally, the negative effect of the Digital Age (DA) on both DROI and BDU suggests that older digital frameworks may impede business performance. It supports arguments in the literature that organisations must continuously adapt and update their digital infrastructure to remain competitive (Yang et al., 2018; Zhang & Wang, 2020).

An important finding of this study is the limited significance of leadership variables (DL, LS), which contrasts with the literature's emphasis on leadership and corporate culture as critical enablers of digital transformation (Munawar et al., 2020; Nasrollahi et al., 2021). This discrepancy may indicate that while leadership is essential in the initial phases of digital adoption, its direct impact on financial and operational outcomes may be less pronounced than technological and financial factors. The digital transformation outcomes influenced by relatively low R^2 values in the regression analysis underscore the complexity of this process. The literature acknowledges challenges such as data integration, governance, and ethical considerations as critical factors shaping digital transformation success (Sestino et al., 2020; Shen & Yuan, 2020). Organisations should adopt holistic digital strategies integrating technology, financial planning, and governance frameworks to maximise the benefits of digital transformation. This study highlighted that firms could optimise digital investments by balancing technology adoption with revenue growth strategies, efficient asset deployment, and financial prudence and suggested exploring moderating factors, including industry-specific dynamics and regulatory environments, that may explore the understanding of digital transformation's impact on business performance.

5. CONCLUSION & RECOMMENDATIONS

With digital transformation and big data technology, companies have never-before-seen possibilities for development and innovation in the current business environment. The study concluded that the difficulties and complications involved in using big data to advance organisational development. While overcoming these obstacles sometimes appears difficult, doing so offers real organisational growth opportunities. Organisations may fully use big data technology by emphasising strong data governance, making talent development investments, encouraging multidisciplinary cooperation, setting clear performance targets, and encouraging algorithmic transparency. Ultimately, adopting new technology is just one aspect of this big data-driven digital transformation path; another is embracing a mentality of resilience, adaptation, and continual development. Organisations must remain flexible, proactive, and dedicated to bringing about good change for their stakeholders as they navigate the digital landscape. Success in this dynamic environment depends on technical aptitude and a solid dedication to moral, responsible, and sustainable behaviour. Organisations may establish themselves as industry leaders and foster innovation, competitiveness, and good social impact for years to come by seizing the possibilities provided by big data technology and confronting its problems head-on. This study faces several limitations, and among a comprehensive mechanism analysis and data collection years, the business inclusion and exclusion criteria are not very clear. Therefore, future research should incorporate broader datasets and alternative methodologies to enhance robustness. A more comprehensive financial constraints analysis should incorporate external and internal funding limitations to capture firms' investment inefficiencies better; alternative econometric models with higher explanatory power should be explored to identify additional determinants influencing data usage in investment decisions. Moreover, sectoral and ownership variations should be examined using industry-specific datasets to improve generalizability and integrate alternative financial indicators, such as market-based metrics and behavioural aspects of decision-making. It could provide a significant understanding of investment inefficiencies by expanding the dataset across different economic contexts, further enhancing the robustness of findings.

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