Key Factors for Successful Digital Transformation in Business Organizations[☆]

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Abstract

Digital transformation in business organisations is about adopting digital technologies to reshape business processes, boost productivity and create value for stakeholders. Despite the potential benefits for firms and other business organisations, digital transformation also entails risks that must be considered in business environments. These risks include the perils of rapid growth, cannibalisation of profitable businesses, security vulnerabilities, and threats to reputation. So, it is crucial to identify factors contributing to the success of business digital transformation efforts. This paper presents findings from empirical studies on publicly listed companies in Brazil that have undertaken digital transformation journeys. These studies analysed factors such as the influence of business sectors, the adoption of agile/lean management methods, and the employment of artificial intelligence tools and other technologies. This paper explores the idea that digitisation technologies and methods differ among various economic sectors. Additionally, it examines whether these sectors experience distinct levels of digital transformation. Furthermore, the paper investigates the existence of correlations between digital transformation intensity and improvements in corporate financial indicators. An automated framework is proposed to identify the key factors contributing to successful digital transformation in business organizations. This framework benefits research and practice, offering analytical and forward-looking approaches for decision-makers and policymakers.

Keywords: Digital Transformation, Business Organizations, Success Factors, Key Performance Indicators, Public Policy

1. Introduction

Information and Communication Technologies (ICTs), especially software technologies, have become crucial today. Businesses rely increasingly on ICTs to automate processes, enhance operations, and improve customer experience and value. This growing dependence on ICTs has led to pressures to improve quality indicators, achieve more robust financial results, and enhance customer satisfaction without sacrificing competitiveness and sustainability.

As a result of the respective technological revolution, a mega-trend emerged among business organisations known as digital transformation (Dean et al., 2012). It involves adopting digital technologies to reshape business processes, boost productivity, and create stakeholder value (Ebert and Duarte, 2018). The IDC (2024) reported that the digital transformation market was valued at approximately \$1.9 trillion in 2022 and projected this value to reach \$3.9 trillion by 2027.

While digital transformation offers various benefits for businesses, it also presents risks that must be evaluated in business contexts. These risks encompass the perils of rapid expansion, potential erosion of

[☆]The assumptions, views, and opinions in this article are solely those of the author and do not necessarily reflect any Brazilian government entity's official policy, strategy, or position.

profitable business segments, security vulnerabilities, and threats to reputation. Therefore, it is crucial to identify factors contributing to the success of business digital transformation efforts.

This paper presents findings from empirical studies on publicly listed companies in Brazil that have embarked on digital transformation journeys. Past studies identified commonly used digitisation technologies and methods (Ebert and Duarte, 2018). The present paper focuses on analysing online information to identify the intensity of digital transformation efforts in various economic sectors. Such a digitisation intensity was determined by textually examining the references to contemporary ICTs and management methods in corporate annual reports (Ren et al., 2023). Additionally, the analysis included factors such as the influence of business sectors, adopting agile/lean management methods, and employing artificial intelligence tools and other technologies.

The reported studies investigated the conjecture that the use of digitisation technologies and methods varies across economic sectors (RQ1). Moreover, these studies examined whether different economic sectors maintain distinct digital transformation levels (RQ2). Furthermore, they delved into correlations between the intensity of digital transformation and the improvement of key financial indicators (RQ3), considered measures of corporate success here. As a result, the paper proposes an automated research framework for identifying the key factors contributing to the success of digital transformation initiatives within business organisations. This framework can benefit research and practice, providing analytical and forward-looking approaches for decision-makers and policymakers.

This paper is structured as follows. Section 2 provides the necessary background on digital transformation. Section 3 presents and discusses the adopted research method. Section 4 provides information about the data analyses conducted and the research outcomes. Section 5 includes a comparison with related work and an analysis of validity threats. The paper's final section briefly discusses the research findings and future research prospects.

2. Background on Digital Transformation

2.1. History

The notion of digital transformation first emerged as a trend in academic research. In the 2000s, Stolterman and Fors (2004) argued that digital transformation would create complex environments that deeply affect daily lives, raising critical questions about how technology should be studied and understood. They advocated for a more reflective and holistic research approach to critically examine ICTs' impact, and assess how they could contribute to or detract from well-being.

Not long afterwards, digital transformation became popular among global consulting firms. For example, Dean et al. (2012) from the Boston Consulting Group launched a Digital Manifesto providing strategic insights for companies and governments to leverage digital opportunities effectively. They argued that companies needed to undergo digital transformation efforts to improve their workforces, processes, and organisational structures. It would involve implementing adaptive strategies, managing legacy businesses, and creating new ones to develop differentiated capabilities. In this way, they would build digital assets and reduce liabilities to capitalise on new opportunities brought about by digitisation. In parallel, many public policy documents were issued covering digitization and related notions, such as Industry 4.0 (Acatech, 2013; MCTI, 2018).

Subsequently, digital transformation was embraced as a mega-trend by companies in the industry, commerce and service sectors, opening the doors for technological innovation, new business models, and cross-industry collaboration (Ebert and Duarte, 2016). So, researchers and practitioners have frequently discussed how technologies could impact businesses due to their early or timely value delivery, usage at larger scales, applications in new domains, and unpredicted technology combinations (Ebert and Duarte, 2018). These ongoing debates still reflect the current state of research and practice.

2.2. Characterisation

Digital transformation is applicable across all economic sectors. For instance, companies in the automotive and manufacturing industries (Gudergan et al., 2017), banking and finance (Schmidt et al., 2017), and telecommunications and health services (Ebert and Duarte, 2018) have frequently implemented digital transformation initiatives. Interestingly, digital transformation can reshape not only their core business processes and models (Kortaba, 2018) but also organisational and technological infrastructures, such as enterprise architectures (Korhonen and Halen, 2017), information systems (Gudergan et al., 2017), embedded, real-time systems and cyber-physical systems (Duarte, 2022).

It is now straightforward to identify the contemporary technological platforms fuelling digital transformation processes, thanks the prior research that offers a comprehensive list of well-known technologies (Ebert and Duarte, 2018): information systems tools, such as enterprise resource planning software (ERP, including business process management, BPM; customer relationship management, CRM; supply chain management, SCM; maintenance, repair and operations, MRO; data warehouse management, DWM; B2B and B2C e-commerce, and many others) and business intelligence (BI) software, apart from blockchain and hyper-ledger technologies for managing cryptocurrencies and smart contracts, to facilitate administrative, operational and financial routines; (big) data science (including data mining and analysis tools), pattern recognition and matching, machine learning (ML, including neural networks) and artificial intelligence (AI) for advanced data and information processing; micro-services, application processing interfaces (APIs) and their ecosystems, as well as robotic process automation (RPA), for software, process and architecture integration and automation; simulation and visualisation tools, augmented and virtual reality (AVR), and digital twins (DT) for amplified user experiences (UX), convergent interactivity and cognition; collaborative robots, autonomous vehicles and interactive drones for industrial and logistics process dynamics; three-dimensional (3D) and additive printing, and flexible or adaptive manufacturing for enhanced production; and sensors and actuators, eventually connected through Internet-of-things (IoT) devices, to facilitate connectivity and ubiquity. These platforms are usually supported by agile methods, such as Scrum and Kanban, and lean techniques, including Kaizen and Six Sigma (Campanelli et al., 2017).

Not every contemporary technology or method can or should be used in the digital transformation of each business sector. Consequently, this paper investigates the use of the technologies and methods above across different economic sectors. Table 1 presents a classification of the aforementioned digitization methods and technologies associated with their presumed demanding business sectors:

Table 1. Methods and Technologies for Digital Transformation.

Category	**Technology / Method Name (Acronym)**	**Presumed Application Sector(s)**
Administration, Finance and Operations Software	Enterprise Resource Planning (ERP) Business Intelligence (BI) Blockchain (BLKC) Hyperledger (HYLG)	All
Advanced Data and Information Processing Tools	(Big) Data Science (BDS) Pattern Recognition and Matching (PATT) Machine Learning (ML) Artificial Intelligence (AI)	All
Software, Processes and Architectures Integration and Automation	Micro-services (MSVC) Application Processing Interfaces (API) Robotic Process Automation (RPA)	All
Amplified User Experience	Simulation and Visualisation Tools (SVT) Augmented and Virtual Reality (AVR) Digital Twins (DTW)	Industry, Commerce
Industrial and Logistics Processes Dynamics	(Collaborative) Robots (ROBT) Autonomous Vehicles (AV) Interactive Drones (DRON)	Industry, Services
Enhanced Manufacturing	3D Printing (THRDP) Additive Printing or Manufacturing (APM) Flexible or Adaptive Manufacturing (FAM)	Industry
Connectivity and Ubiquity	Sensors (SENS) Actuators (ACTU) IoT Devices (IOTD)	All
Management Methods	Agile Methods (AGIL) Lean Methods (LEAN)	All

Source: Adapted and expanded by the author from (Ebert and Duarte, 2018).

3. Methodology and Research Design

3.1. Information About Brazilian Companies

Brazil has a large and diverse economy, with many companies undergoing digital transformation. Thus, the country is a convenient representative location for empirical studies on the digital transformation of business organisations. According to the latest information released by the Brazilian Institute of Geography and Statistics (IBGE, 2023), there were 8.36 million companies in Brazil at the end of 2022. Still, those with high levels of transparency are registered with CVM, the Brazilian Securities and Exchange Commission. As of the end of 2023, there were 2594 firms registered with CVM (2024a).

The companies which comply with the highest levels of corporate governance have their shares listed and traded in five specific segments of the Brazilian Stock Market (called B3, formerly known as Bovespa). These five segments are called New Market, Level 1 and 2 (in which mature companies usually get listed), and Bovespa Plus 1 and 2 (market segments specific for small and medium-sized enterprises, SMEs). To ensure the highest possible data quality level, only companies publicly listed in these segments of B3 were considered in the conducted studies. So, these studies investigated just 252 firms (B3, 2024).

The CVM makes available online two kinds of standardized information regarding each registered company: annual reports (FREs, according to the CVM terminology) containing strategic, operational and financial information (2024b), and financial statements (DFPs, in the CVM terminology), which comply with international accounting standards (2024a). Due to the recency of digitisation processes among business organisations (Dean et al., 2012), only the most recent reports made available between 2015 and 2024 were studied, reflecting the decade from 2014 to 2023.

Regrettably, there were no recorded filled DFPs in the CVM datasets for three companies under investigation, resulting in their exclusion from the analyses. Consequently, the reported studies investigated only 249 companies' complete data, as detailed in Table 2:

Table 2. Summary of Company Selection Process.

Company Stratum	Number of Companies
Companies Existing in Brazil	8 360 336
Firms Registered with CVM	2 594
Companies Listed in Specific Segments of B3	252
Firms with Missing Financial Reports	3
Total Number of Analysed Companies	249

Source: Table created by the author.

3.2. Economic Sectors and Their Digital Transformation Intensity Levels

The CVM classifies registered companies according to their primary business activities. This classification was created to develop the Brazilian capital market by facilitating comparisons between similar companies and mitigating information asymmetry risks. The classification offers comprehensive market information to investors and the Brazilian society. Table 3 presents the breakdown of the publicly listed companies studied, classified according to their respective business sectors. Each economic sector is represented in the table by a numerical value, which is captured by the categorical variable **SECT**.

Table 3. Classification of Studied Companies by Business Sector.

SECT	Economic Sector	Frequency	Quantity
1	Accommodation and Tourism	0.40%	1
2	Agriculture	3.97%	10
3	Banking	4.37%	11
4	Construction, Building Materials and Decoration	13.49%	34
5	Commerce (Wholesale and Retail)	14.68%	37
6	Education	2.78%	7
7	Electric Energy	7.54%	19
8	Financial Intermediary	0.79%	2
9	Food and Beverage	3.17%	8
10	Information and Communication Technologies	8.73%	22

SECT	Economic Sector	Frequency	Quantity
11	Insurance Companies and Brokers	2.38%	6
12	Machinery, Equipment, Vehicles and Parts	5.56%	14
13	Medical Services	3.97%	10
14	Metallurgy and Steel Industry	2.78%	7
15	Mineral Extraction	1.59%	4
16	Oil and Gas	3.17%	8
17	Packaging	0.40%	1
18	Petrochemicals and Rubber	1.19%	3
19	Pharmaceutical and Hygiene	1.98%	5
20	Pulp and Paper	0.79%	2
21	Sanitation, Water and Gas Services	2.38%	6
22	Receivables Securitization	0.00%	0
23	Services, Transport and Logistics	8.73%	22
24	Stock, Commodities and Futures Exchange	0.40%	1
25	Textile and Clothing	3.97%	10
26	Toys and Leisure	0.79%	2

Source: Adapted from (CVM, 2024a) and expanded by the author.

Although they are present in CVM's classification, holding companies do not explicitly appear in Table 3, as their primary investment sectors are considered instead.

Considering these definitions, it is possible to note that Table 1 anticipated the formulation of the first research hypothesis investigated in the conducted studies in connection to RQ1:

(H1) The use of digitisation technologies and methods varies significantly across economic sectors.

It is now feasible to formalize a specific design decision in the studies that were conducted. Each company's current digitisation index, called **DXI** here, was computed by counting the number of references to the technologies and methods listed in the second column of Table 1 in the respective annual reports. The respective digital transformation level, called **DXL** here, was determined by the application of the symmetric logarithm transformation, that is, multiplying the sign of the **DXI** index (positive in this case) by the application of the natural logarithm to the number one added to the absolute value of the index[1].

As a consequence of these definitions, another research hypothesis could be formulated by connecting the determined average digitisation levels to the respective business sectors:

(H2) Different economic sectors maintain significantly distinct average digital transformation levels.

It is important to mention that the digitisation index and level were used interchangeably in formulating H2. Moreover, given its importance to the research subject, the term "digital transformation" (represented by the acronym DX here) was also counted and weighed three times higher than the single weight of an individual technology and method in the computation of **DXI** and **DXL**. The conducted studies also considered that any company scoring in three or more categories of Table 1 in a specific year (or which mentioned "DX" explicitly in their reports) presented sufficient digital transformation evidence (represented by a boolean construct named **DXE** here) in that year.

3.3. Measuring Key Success Factors

A series of standard key financial indicators (KPIs) were utilised to evaluate the performance of the studied companies (Fridson and Alvarez, 2011) and examine the impact of their digital transformation efforts on financial indicators over time. Their annual values were calculated using the standardised, consolidated financial statements filed with CVM. Table 4 presents the categories, acronyms, names and definitions of these key indicators:

[1]The conducted studies adopted the logarithmic scale to make data more accessible to analyse, compare, and interpret when dealing with a wide range of values and zeroes. The logarithm application corresponds to a monotonic transformation used to normalise values and standardise relationships among variables. The transformation application is emphasised throughout the paper whenever it is used.

Table 4. Adopted Key Financial Indicators.

Category	Acronym	Indicator Name	Definition (where i refers to a specific year)
Operations	**N_G_R**	Revenue Growth Rate	$Total\_Revenue_i$ / $Total\_Revenue_{i-1}$
	GR_M	Gross Margin	$Gross\_Profit_i$ / $Total\_Revenue_i$
	OP_M	Operating Margin	$Income\_Before\_Financial\_Result\_\&\_Taxes_i$ / $Total\_Revenue_i$
Assets	**INV_A_R**	Inventory to Assets Ratio	$Inventory_i$ / $Total\_Assets_i$
	INT_A_R	Intangibles to Assets Ratio	$Intangibles_i$ / $Total\_Assets_i$
Finances	**CUR_LIQ**	Current Liquidity	$Current\_Assets_i$ / $Current\_Liabilities_i$
	RET_EQ	Return on Equity	Net_Profit_i / Net_Worth_i

Source: Table created by the author adapted from Fridson and Alvarez (2011).

This set of key financial indicators was chosen due to the potential reflection of digitisation on the respective general ledger account balances. The revenue growth rate helps assess each company's pace of growth. Gross and operating margin indicators are helpful in evaluating a business's annual profitability while excluding net financial results. The inventory and intangible to total asset rate indicators access the relative importance of specific asset types that may be directly influenced by digitisation. The current liquidity ratio evaluates each company's capability to meet short-term obligations. In turn, the return on equity ratio allows one to analyse the proportion of losses and profits compared to the company's worth value and value generation process.

The chosen KPIs are relatively independent in evaluating a company's performance from various perspectives, also called evaluation categories. In particular, digital transformation may boost sales and reduce costs and related expenses, justifying the study of operational indicators such as **N_G_R**, **GR_M** and **OP_M,** respectively. Digitisation may also help form intangible assets and better manage them in conjunction with physical inventories, capturing digitisation phenomena like the transition to the digital economy through increases in **INT_A_R** and reductions in **INV_A_R,** respectively. In particular, the intangible assets recognised in accounting books as capitalised R&D expenditures, such as intellectual property and brand values, were considered relevant due to their direct connection with the studied digitisation technologies. In addition, digitisation may help improve working capital management and generate positive shareholder equity returns, justifying the study of financial indicators such as the short-term **CUR_LIQ** and the long-term **RET_EQ,** respectively.

As a result of the choice of these KPIs, a third research hypothesis was formulated correlating digital transformation levels to the possibly impacted financial indicators:

(H3) Digital transformation intensity positively contributes to improved financial performance.

In this case, the conducted studies considered a company financially successful if it showed a marginal improvement in the compounded change ratio of the studied indicators in a specific year compared to the previous year, represented by the **FII** index here. This ratio was used to define the financial improvement level variable **FIL** by applying a symmetric logarithm transformation. This paper calls **FIE** the resulting financial improvement evidence construct.

It is important to mention that the employed financial indicators possess high reliability ($> 90\%$) because they are derived from data disclosed in the financial statements of publicly listed companies, which in general adhere to rigorous standards of compliance, governance, and ethics (Jianu and Jianu, 2021).

3.4. Research Methodology

The studies that were conducted involved obtaining and clearing administrative records from CVM and filtering the respective datasets afterwards to focus only on companies listed on B3. Next, data from the respective annual financial reports were tabulated using spreadsheets. With the required classification and financial data, the necessary annual reports were collected manually from CVM's site between April and September 2024, totalling nearly 35 GB of raw data. Annual reports were transformed into text, and digitization data was extracted and processed using Linux shell commands and Python scripts. Financial and technical indicators were then calculated using spreadsheets. In this way, it was possible to organise the formulated hypotheses and the collected data according to the logical map presented in Figure 1.

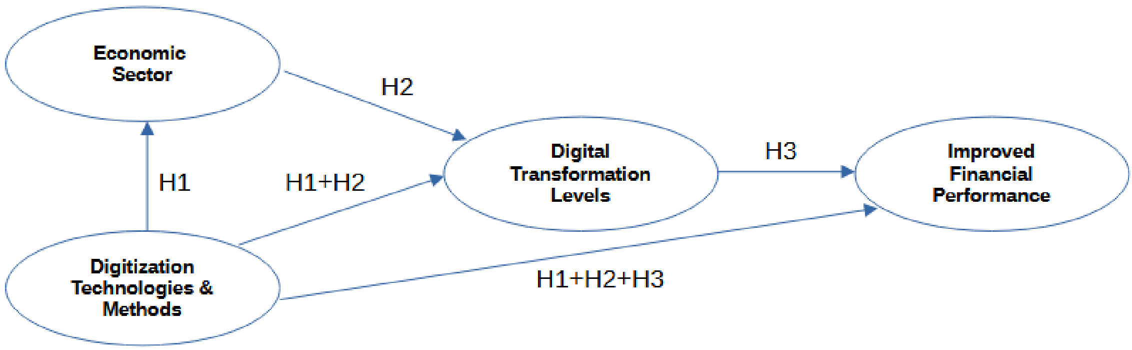

Figure 1. Logical Model of Improved Financial Performance Enabled by Digital Transformation.

4. Analyses and Empirical Results

This section presents the descriptive statistics, correlational analyses, and hypotheses testing developed for validating H1 and H2. Subsequently, structural equation modelling (SEM) is presented to explore the theoretical design space and investigate the validity of H3. These studies also assess the robustness of the respective research findings.

4.1. Descriptive Statistics

This section uses descriptive statistics to analyse **DXL, DXE**, **FIL** and **FIE** from 2014 to 2023.

Table 5. Descriptive Statistics of DXL.

DXL	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
N	157.00	158.00	168.00	176.00	187.00	223.00	250.00	252.00	252.00	251.00
SD	0.94	0.98	1.00	1.01	1.08	1.06	1.05	1.05	0.98	1.01
Max	4.49	5.26	5.49	5.43	5.51	5.35	5.39	5.37	5.20	5.22
Top	4.11	4.76	4.33	4.31	4.80	5.03	5.32	5.35	5.17	5.21
3^{rd} Q	2.30	2.56	2.56	2.69	3.00	3.18	3.38	3.46	3.33	3.33
Mean	1.76	1.94	2.02	2.13	2.38	2.58	2.72	2.79	2.73	2.71
Median	1.79	1.95	1.95	2.14	2.40	2.48	2.64	2.77	2.71	2.71
1^{st} Q	1.10	1.10	1.39	1.61	1.79	1.95	2.08	2.20	2.11	2.08
Bottom	0.00	0.00	0.00	0.00	0.00	0.10	0.13	0.31	0.27	0.20
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Table created by the author.

The increasing number of **DXL** observations over the years indicates that more and more companies have filled annual reports with the CVM, as shown by the values of N in Table 5. Their compliance requirements after IPOs drives this trend. The increase in the mean value of **DXL** shows that these companies have become increasingly interested in digital transformation technologies and methods. The average digitisation index, computed from the citations in each annual report, varied from 8.41 to 23.45 between 2014 and 2023 (corresponding to the exponentiation of the values in Table 5 following Mean). Although some companies in the studied sample did not engage at all in digitisation efforts over the years (Min = 0), the highest index of 245, calculated from a single report, was recorded in 2018. The primary mean value of ten was reached that year and has remained above this threshold. The stable standard deviation (SD) of the transformed index, close to one, indicates low variability in the transformed data, whereas the original untransformed data showed some relevant variability. The wide range between the minimum and maximum values suggests varying levels of digitisation among the studied companies.

Table 6. Descriptive Statistics of DXE.

DXE	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
N	157.00	158.00	168.00	176.00	187.00	223.00	250.00	252.00	252.00	251.00
SD	0.39	0.43	0.47	0.48	0.50	0.49	0.46	0.44	0.44	0.45
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Top	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3rd Q	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mean	0.19	0.24	0.34	0.37	0.49	0.60	0.69	0.73	0.74	0.73
Median	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00
1st Q	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bottom	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Table created by the author.

Concerning digitisation evidence among the studied companies, it is noticeable in Table 7 that, since 2018-2019, when the mean value of **DXE** crossed 0.5, most companies have engaged in digital transformation efforts. However, looking at individual cases in the sample, it became clear that, for a few companies, this evidence was transitory; for some others, digital transformation was not an irreversible tendency, while, for most of the companies in the dataset, digital transformation was a strategic decision that remained effective until the end of the studied period.

Table 7. Descriptive Statistics of FIL.

FIL	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
N	150.00	149.00	153.00	160.00	167.00	175.00	208.00	229.00	239.00	241.00
SD	0.00	1.58	1.49	1.93	1.68	1.49	1.83	1.64	1.4	1.56
Max	0.00	5.49	6.52	7.06	7.56	6.78	7.59	6.91	5.81	8.01
Top	0.00	2.6	2.55	3.26	3.26	2.83	3.03	4.3	2.35	2.94
3rd Q	0.00	0.65	0.67	0.92	0.99	0.8	0.89	1.41	0.62	0.82
Mean	0.00	-0.18	0.08	0.15	0.35	0.09	0.06	0.49	-0.01	0.04
Median	0.00	-0.04	-0.04	0.12	0.13	-0.02	-0.05	0.11	-0.06	0
1st Q	0.00	-0.66	-0.58	-0.63	-0.53	-0.55	-0.54	-0.52	-0.54	-0.58
Bottom	0.00	-2.61	-2.46	-2.97	-2.81	-2.57	-2.69	-3.4	-2.27	-2.69
Min	0.00	-8.27	-4.29	-7.34	-5.22	-5.46	-10.5	-3.96	-5.99	-8.38

Source: Table created by the author.

Again, in the **FIL** case, more and more companies have filed financial reports with CVM to meet the requirements for remaining listed on B3. However, the financial performance of the studied companies in this period was not bright due to exogenous events between 2015-2018 and 2020-2022. From 2015 to 2017, an economic crisis in Greece almost led the country to leave the European Union. In 2016, the UK decided to leave the economic block after a public referendum, something implemented in 2020. These events directly affected Europe and the Brazilian economy indirectly. Moreover, between 2020-2022, the COVID-19 pandemic led to social distancing and economic lockdowns worldwide, disrupting supply chains, reducing consumption and generating an international economic crisis. Consequently, the studied companies' overall financial performance was negative in the period, as seen through the small mean values of the **FIL** variable in Table 7. The corresponding period was financially unstable, as observed through the high and varying **FIL**'s standard deviation values.

Table 8. Descriptive Statistics of FIE.

FIE	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
N	150.00	149.00	153.00	160.00	167.00	175.00	208.00	229.00	239.00	241.00
SD	0.00	0.42	0.43	0.46	0.48	0.46	0.45	0.48	0.41	0.45
Max	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Top	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00
3^{rd} Q	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00
Mean	0.00	0.23	0.24	0.31	0.35	0.30	0.28	0.36	0.22	0.29
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1^{st} Q	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bottom	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Table created by the author.

During the studied period, between 22% and 36% of the investigated companies presented evidence of positive financial performance each year, as perceived through the average value of the **FIE** boolean variable in Table 8.

4.2. Correlational Analyses and Hypotheses Testing

The tables in the previous sections show that the collected data is categorical, not normally distributed and has null values. In this situation, the Φ coefficient (Cramér's V correlation), calculated using the Chi-Square method (Rosner, 2010), can be used to assess the existence of a statistically significant general association between business sectors and the digitisation technologies and methods they adopt. A null or small value of Φ corresponds to no or weak association, whereas values near one suggest a strong association. A post hoc analysis can also be performed based on the computed standardised residues that estimate the distinction between expected and observed values to investigate specific connections between digitisation technologies and methods and the business sectors adopting them.

The respective statistical analysis was conducted using the R statistical package and the vcd library. First, the null value was substituted by the negligible value 0.01 to apply the Chi-square method with automated support. Then, the $\chi^2 = 21154$ statistics was calculated with 625 degrees of freedom, yielding a p-value of 2.2×10^{-16}. The corresponding Cramér V correlation coefficient was $\Phi = 0.155350$, demonstrating no general association between business sectors and their adoption of digitisation technologies and methods. An additional analysis was performed using *10 000* simulated datasets to assess the influence of the 0.01 imputation in the case of no observations. In this kind of simulation, the total counts in each row and column in the respective contingency table are preserved, but the arrangement of counts is randomised. The resulting values of χ^2 and Φ were the same, but the calculated p-value was 9.999×10^{-5}. This result indicates that the imputation process did not affect the analysis results.

Table 9 presents the contingency data, corresponding to the respective raw digitisation index summation, with the significance levels obtained from the computed standardised residues. The significance of each correlation is presented visually using asterisks next to each citation count data. In the table, a single asterisk denotes significance at the 5% level, a double at the 2.5% level, and a triple at the 1% level. As seen in the table, the utilisation of the diverse digitisation technologies and methods across business sectors is not uniform, varying significantly from case to case. This investigation confirms H1.

The table shows that each economic sector has relied on a small set of most significantly adopted technologies and methods. By far, ERP software has been the most frequent digitisation technology for companies in the commerce, textile, and clothing sectors. It is also significantly frequent among food and beverage, pharmaceutical and hygiene, and package companies. Companies in these sectors have migrated from traditional business models to the digital economy, justifying their reliance on software like ERP, including e-commerce. Indeed, considering business sectors, companies in the commerce, information and communication technologies sectors are the most digitised. Moreover, artificial intelligence and business intelligence software are also often used, though less frequently than ERP software, with a broader distribution across various business sectors. Surprisingly, although they were previously identified as necessary for digitisation (Ebert and Duarte, 2018), some technologies have not been explicitly used, such as Hyperledger and automated pattern matching and recognition. The limited use of these technologies

Table 9. Contingency Table with Sectoral Digitisation Indexes and Their Significance Levels.

SECT	ERP	BI	BLCK	HYLG	BDS	PATT	ML	AI	MSVC	API	RPA	SVT	AVR	DTW	ROBT	AV	DRON	THRD	PAPM	FAM	SENS	ACTU	IOTD	AGIL	LEAN	DX
1	61	11			2			4		2														2	1	41***
2	251	27			6			286***		1	9***						21***				4			20	4	8
3	339	316***	18**		98***			313***	4***	83***			2		10						13		8	174***	101***	216***
4	1372	148	2		13			681***		100***			8		27***		8				36	2	17	130	128***	127
5	6901***	305	11		179		9***	512	2	16	8	9***	36		7	3	9				57		101	232	58	897***
6	331	46			95***			82	1		9***		28***		8	8***					9	5***	4	111***	43***	297***
7	771	442***	14		58			853***		1	16***		11		7	8	79***				334***		29	48	33	50
8	216	22	12***		66***			39		40***													4	7	8	7
9	320**	20	14***		25			82							3									49***		26
10	2885	194	124***		335***		4	506	9***	47	20*		23		24	4	43				31	3	467***	233	72	511**
11	212	82***	2		18			65		7	1		2								1			50***	6	80***
12	562	109*			46			81		15	8**		1		13*	6**	87***	6***	6***	4***	113***	15***	147***	71	122***	32
13	469	94***			39			186***		2	9***		1		34***			3*			7		5	45	30	64
14	336	14						161***		8	1				1						24***		5	16	29***	6
15	142	47***	1		5			121***									4	2**	2***					17	34***	13
16	318	36			31			94		78***	1			13***	20***	18***	10				20	1	12	53*	14	201***
17	74***	1						6							1									4		12
18	30	60***	3		2			21		39***					3*			22***	11***		22***					4
19	389***	28			6			24		14**														31*	7	14
20	41	13*			2			44***					1				4**				2					12
21	147	11	1		7			50*			1										12**	1	14**	6	3	11
22																										
23	1226**	117	1		36			448***		2					4	7*	24				10		21	95	72**	116
24	30	4	3**		20***			23*																16***	5	4
25	1197***	39	5		30			44					2		2						9		2	61	63***	149
26	46	1			8			93***																2	1	9

Source: Table created by the author from the output of the `happa2` function of the R `vcd` library.

likely stems from their frequent integration into other solutions, such as Blockchain, ERP and other advanced data processing tools.

Regarding the reliability of these findings, Kappa statistics can be developed. In this case, statistics can estimate the difference between the observed and expected probabilities of outcome concordance in the original result compared to that obtained through simulation. Using the irr library from the R package, it was possible to determine $\kappa = 1$ with a p-value of zero. This result indicates excellent reproducibility and provides strong evidence that the observed agreement is statistically significant and not due to chance (Rosner, 2010). In other words, there is strong evidence that the adopted experimental design is reliable and reproducible.

Concerning H2, there is interest in investigating the relationship between a continuous variable and a categorical variable. The categorical variable represents independent economic sectors, while the continuous variable denotes digital transformation levels, which do not follow a normal distribution. In this situation, a non-parametric test like the Kruskal-Wallis test is required. This test ranks all observations, groups them, and compares their average ranks. The null hypothesis indicates that all groups have the same mean (share the same rank), suggesting no statistically significant distinctions. The main hypothesis is that different groups have distinct average values.

As the test is effective only with groups of five or more observations, data from smaller groups were combined into a distinct category containing a variety of observations from different economic sectors. The Kruskall-Wallis test was applied using an R script in the present case. Ultimately, the 249 observations were distributed in 18 groups of different sizes. The Kruskal-Wallis test produced a statistic $H = 82.0420$, with 17 degrees of freedom, yielding a p-value of 1.66×10^{-10}, which indicates high statistical significance, thus confirming H2. Post hoc analyses were helpful in determining which groups differed. It was possible to compute a matrix with the group comparisons using the Wilcoxon rank-sum test for multiple comparisons, along with the Benjamini-Hochberg adjustment to decrease the false discovery rate. The analysis showed that the digitisation levels of the ICT sector (numbered 10) were significantly higher than the other sectors. Many other significant differences were found, but the most pronounced highlighted substantial distinctions in the level and variance of digital transformation between the commerce (number 4) and construction (number 5) sectors. The box plot in Figure 2 helps visualise the data distribution for each group and the distinctions in their mean values.

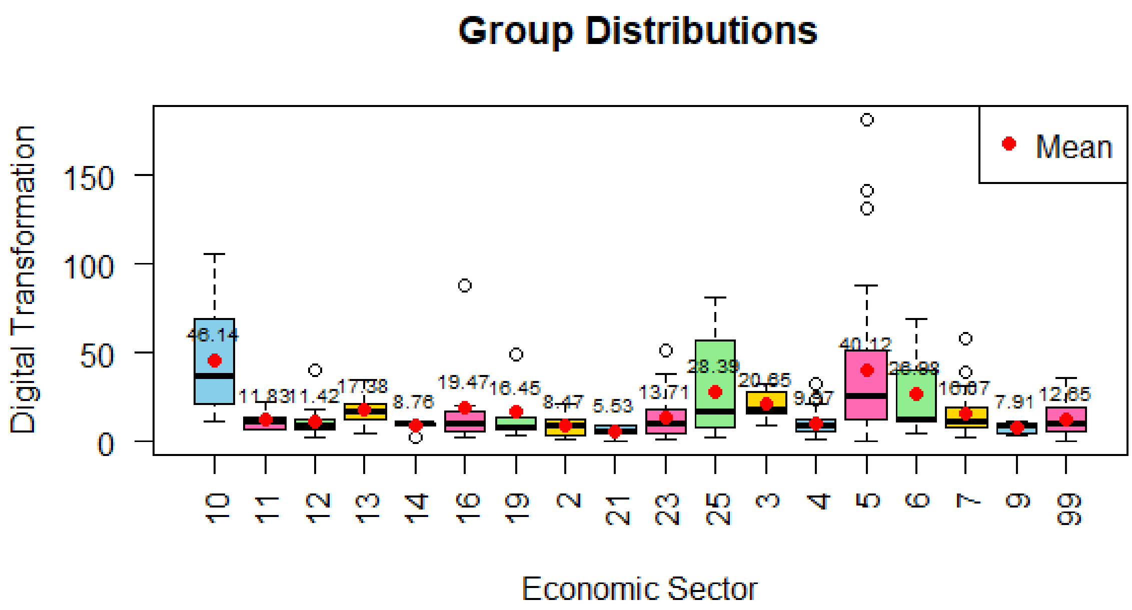

Figure 2. Box Plot with the Distribution of Digital Transformation Levels Across Economic Sectors.

The consistency and robustness of the findings related to H2 were assessed by calculating the respective effect size. The eta-squared statistics were determined (η^2) for Kruskal-Wallis tests, estimating the proportion of variance explained by group differences. The calculated value $\eta^2 = 0.278$ indicates the proportion of the total variance in the measurements that can be attributed to group differences. This value indicates a moderate effect size, suggesting that differences among economic sector groups account for approximately 27.8% of the variance in the digitisation level variable. This implies that the economic sector groups being compared significantly differ in terms of their respective digitisation levels measurements.

4.3. Structural Equation Modelling

The H3 hypothesis is investigated using a specific directional formulation. Digital transformation was the hypothesised source, and sound financial performance was the conjectured outcome in this setting. The factors that affect digital transformation and financial performance are then the focus subjects of study. The collected data provided some correlations between these factors, which required developing of a confirmatory analysis that digital transformation positively impacted financial performance.

Structural equation modelling is well suited to study this kind of relationship (Hair et al., 2006). Indeed, SEM allows one to pinpoint the impact's directionality, accommodates interaction modelling, correlates independent variables, and studies non-linearity and correlated error terms (Naji et al., 2024). So, the formulated logical model was unfolded in a dependence diagram, as presented in Figure 3, to support the required investigation. This thorough conceptual model took into account the observed variables (in boxes) with their error terms (circles), and latent constructs with their error terms (ovals) with the assumed relationships between them (arrows).

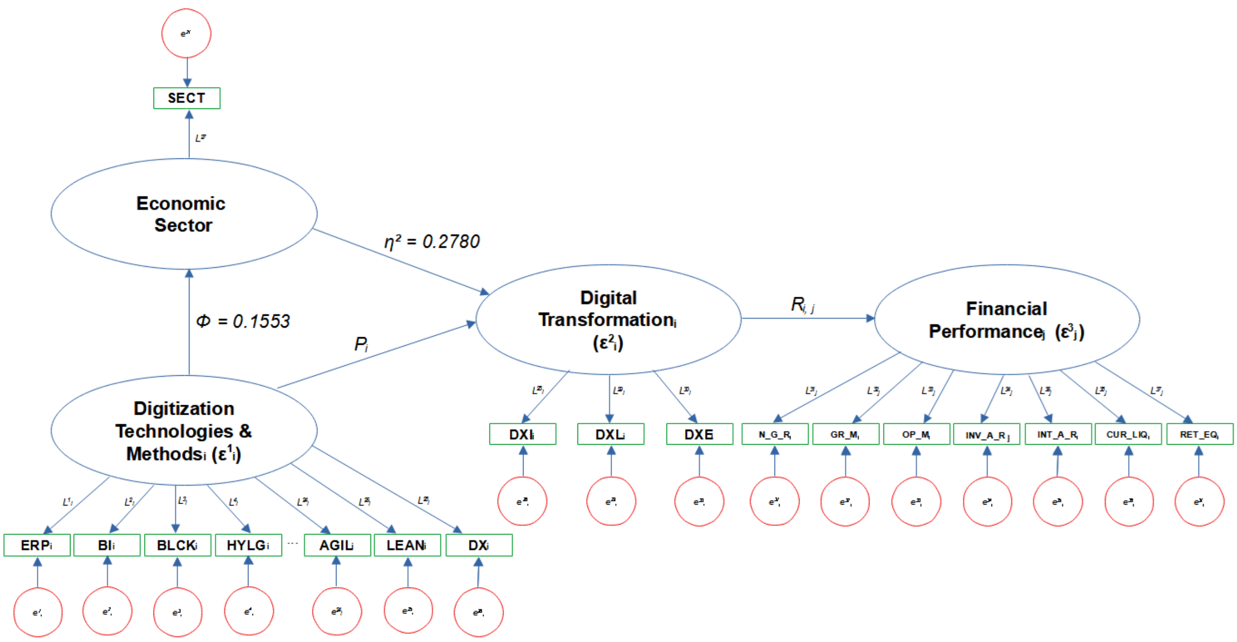

Figure 3. Dependence Diagram of Financial Performance in Relation to Digital Transformation.

The R statistical package with the lavaan library (Rosseel, 2012) was selected to develop the required analyses. Lavaan is an accessible and widely used tool for longitudinal SEM, which can handle continuous and non-normal data. When using lavaan, methods like MLR (Maximum Likelihood estimation with Robust standard errors) can be adopted. This method deals with non-normally distributed data by providing robust adjustments to standard errors, test statistics, and chi-square values. MLR performs adequately with samples above 200 observations and can handle longitudinal models with multiple latent constructs. So, the MLR estimator was selected to treat the non-normal distribution underlying the studied data and avoid inaccurate estimations. In addition, the FIML (Full Information Maximum Likelihood) method was used to handle missing data. It is particularly effective for longitudinal data analysis because it assumes that data is missing at random.

The model shown in Figure 3 can be divided into three sections. The first section illustrates the intensity of relationships that have already been established using other methods (cf. Φ and η^2). The second section is related to the influence of contemporary technologies and methods on digital transformation. It is represented as a static relationship and the intensity for a year i can be calculated by estimating the value of the relation P_{i}. Finally, the model has a correlational (three-year) lagged part, which relates through $R_{\text{i,j}}$ the financial performance of ccompanies in a year j to their digital transformation efforts in the years $i \leq j$. So, the longitudinal study concerning the impact of digitisation on financial performance considered the regression and covariation between variables and their temporal connections.

SEM adopts an investigation methodology that iteratively evaluates the fitness of the observations in a measurement model against a structural (theoretical) model, providing modification suggestions to improve model fitness. Initially, since **FIL** and **FIE** mediate the effect of the financial indicators on the latent variables, the structural model was simplified without losing essential information by removing these indicators. Moreover, the auxiliary variables **DXI** and **FII** presented in Figure 3 were also excluded from the analysis as the model already captured digitisation from two different perspectives, using the pairs of variables **DXL** and **FIL**, as well as **DXE** and **FIE**. These pairs of variables gave rise to similar alternative models, which were evaluated competitively.

SEM requires that variables have at least two levels (distinct categories) to perform fitness analyses because it cannot estimate variances or relationships for single-category variables. However, some variables in the dataset had single values or presented low variance. So, these variables did not contribute meaningful information to the analysis and must be excluded from the model. Due to this, all the variables in the original model referring to the year 2014 had to be excluded. The exclusion procedure was also applied to the variables **HYLG** and **PATT**, which have no observations, and to **ML**, **MSVC**, **SVT**, **DTW, AV, THDP, APM, FAM** and **ACTU**, which have observations from a small number of companies ($< 5\%N$). Consequently, the model in Figure 3 was revised to remove all these variables.

Subsequently, it is necessary to estimate the load factors (L_{i}) of the remaining variables with the respective errors (e_{i}), the latent constructors (with their error factors $\epsilon^k, 1 \leq k \leq 3$), and the directionality and power of the hypothesised relationships (P_{i} and $R_{\text{i,j}}$), all of which explicit parameters of the model. The logarithm transformation was applied to the observations of the remaining variables in each model to facilitate the fitness process. The process continued by exhaustively examining each variable's factor loadings and modification indexes to adjust their contribution to the overall model.

An additional issue related to some variables became evident in the model-fitting process. Specifically, there were variables in the model denoting digitisation technologies and methods with low calculated factor loadings relative to other variables that have more significant roles. So, the variables with load factors consistently below 0.400 must be eliminated from the model as they could undermine its integrity (Hair et al., 2006). In the present case, the following variables had to be eliminated: **BI**, **BLCK**, **BDS**, **API**, **RPA**, **AVR**, **ROBT**, **DRON**, **SENS**, **IOTD, AGIL** and **LEAN**.

Iteratively, to refine the model at hand further, a sequence of changes and Goodness-of-Fit (GOF) evaluations were performed to assess how well each variable in the current model aligned with the underlying theoretical definitions. This process aimed to ensure model validity and appropriateness. As a result, the model suffered revisions at each step to remove unnecessary variables, formalise newly identified covariance relationships and allow the computation of all required data, as above. In the present case, many lagged covariance arcs were added to the model to denote the extent to which each two measurement variables change together over time. Modifications in the model accounted for covariances relating the same variable over time or logical relationships between the theoretical concepts they represent, for instance, connecting **ERP** and **AI**, and these to digital transformation in general (**DX**). At the end, the only digitisation technology and method variables maintained in the model were **ERP** (with load factor and standard error $L_i^1 \pm e_i^1 \subseteq [0.928 \pm 0.033, 0.973 \pm 0.046]$), **AI** ($L_i^8 \pm e_i^8 \subseteq [0.362 \pm 0.103, 0.446 \pm 0.065]$) and **DX** ($L_i^2 6 \pm e_i^i \subseteq [0.233 \pm 0.208, 0.554 \pm 0.058]$).

A final post hoc GOF evaluation of the produced model confirmed its appropriateness and validity. The assessment of the model was based on the Chi-square Test of Model Fit (χ^2), in which a non-significant χ^2 value suggests a good fit, meaning an insignificant discrepancy between measurement and structural model. The model's fitness with respect to the respective theoretical formulation was evaluated through the Robust Comparative Fit Index (CFI) and Robust Tucker-Lewis Index (TLI). This process also used the Standardised Root Mean Square Residuals (SRMR) to estimate the number of errors in the model, Root Mean Square Error of Approximation (RMSEA) to estimate the average difference between observed and predicted correlations and Relative Chi-square (χ^2/df), a model fitness measure adjusted for complexity, based on the calculated degrees of freedom. Table 11 presents this analysis.

Table 10. GOF Assessment for the Adjusted Structural Models.

Robust Assessment Test	Acronym	Calculated Values (Model DXL + FIL)	Calculated Values (Model DXE + FIE)	Normal Acceptance Threshold
Chi-square Test of Model Fit	χ^2	$1621.81 (p = 0.0)$	$1121.18 (p = 0.0)$	$p > 0.05$
Robust Comparative Fit Index	CFI	0.921	0.936	$0.90 < CFI$
Robust Tucker-Lewis Index	TLI	0.876	0.900	$0.90 < TLI$
Standardised Root Mean Square Residuals	SRMR	0.126	0.104	$SRMR < 0.08$
Root Mean Square Error of Approximation	RMSEA	0.083	0.063	$RMSEA < 0.1$
Relative Chi-square	χ^2/df	1621.81/633	1121.18/639	$1.0 < \chi^2/df < 3.0$

Source: Table created by the author from the output of the fitMeasures function of the R laavan library.

Table 11 shows that most assessments surpassed the minimum acceptable threshold. In the case of model **DXL + FIL**, the Chi-square test p-value spotted a discrepancy between the measured data and the structural model, but the accuracy of this test is susceptible to sample size. The calculated CFI and TFI indexes provided evidence of a low but acceptable fit. In particular, the TLI value slightly under the acceptance threshold was clearly a consequence of the high complexity of the developed longitudinal model, whose variables needed to cover all the years under analysis. The SRMR value indicated a less-than-ideal fit, but the RMSEA was acceptable. The computed dfs illustrated the complexity of the model, while the Relative Chi-square test showed that the model fitted the measurement data. Concerning the assessment of model **DXE + FXE**, the results were better. Still, reliability concerns were raised, even though using **DXE + FIE** instead of **DXL + FIL** corresponds to a discretisation procedure that reduces variability.

The robust Omega test was used to evaluate the internal validity and reliability of the fitting procedures, as it estimates the extent to which variables defining a latent construct are correlated. The test provides accurate estimates when the variables have varying contributions to the underlying construct. The test result varies between zero and one, but values greater than 0.70 are acceptable. In the case of model **DXL + FIL**, $\omega_i \in [0.5343986, 0.7312601]$, with most of the years exceeding the 0.70 reliability threshold. However, regarding the model **DXE + FXE**, $\omega_i \in [0.1919685, 0.6695047]$. Since the reliability test failed for all the years under investigation, the second model had to be discarded.

Concerning the relationships in the model, the SEM process also determined statistically significant load factors for $P_i \pm \epsilon^{P_i} \subseteq [1.424 \pm 0.113, 1.806 \pm 0.213]$. They reflected the strength of the respective relationships and provided evidence that using of digitisation technologies and methods is a strong predictor of corporate digitisation levels. The fact that zero did not belong to any computed confidence interval highlighted the robustness of this finding. Regarding the other relationships between digitization and financial performance, $R_{ij} \pm \epsilon^{R_i,j} \subseteq [-0.057 \pm 0.063, 0.154 \pm 0.086]$ were not determined with statistical significance and generally had very modest values, as indicated by the respective high p-values and small standardised estimates. The lack of significant correlations and the high variability over the years reinforced the conjecture that exogenous events may have influenced the relationship between digitalization and financial outcomes in these periods. Consequently, H3 was not confirmed.

5. Related Work and Threats to Validity

5.1. Related Work

Since 2005, the survey TIC Empresas (CETIC.BR, 2023) has examined the ICT use among Brazilian companies with more than ten employees. Conducted biannually with randomised sampling, it assesses a substantially larger number of companies than the studies reported here using convenience sampling. The survey is based on questionnaires that collect data on a restricted set of technologies (namely big data, industrial and service robotics, 3D printing, Internet of Things and artificial intelligence). Incidentally, the Brazilian government used TIC Empresas to estimate that, in 2023, just 23% of all Brazilian industrial companies had digitalised their processes (MDIC, 2024). This estimation was based on the premise that at least one digitisation technology was adopted yearly. In contrast, in the sample studied here, there was digitisation evidence for 51% of the industrial companies, all of the large size, illustrating the differences between these studies. More specifically, the studies reported herein used a data collection process based on text mining. An ample set of digitisation technologies and methods was investigated, with more stringent digitisation criteria. In addition, the reported studies went beyond TIC Empresas by calculating a digitalisation intensity level for each company and correlating it to the studied companies' financial indicators.

Many papers have examined similar research questions regarding the Chinese economy. Ren et al. (2023) investigated the impact of digitisation on the performance of Chinese-listed manufacturing companies. They extracted keywords related to digitalisation from annual reports between 2009 and 2020. Factors like company size, age, the board of directors' education level, the proportion of fixed assets to the company's total assets, and the degree of enterprise digitisation were studied. Their paper uses regression models and robustness tests to support the idea that digitisation can enhance corporate performance. Zhao and yan Liu (2024) studied Chinese manufacturing SMEs based on data collected in direct surveys and annual reports (2019 and 2020), which were analysed using structural equation modelling. They concluded that digitisation technologies positively affect a firm's supply chain digital integration capability, which in turn positively enhances firm financial performance. However, they identified that government support generates perceived antagonistic effects. Sun et al. (2024) studied the intrinsic influence of digital transformation on the sustainable growth of listed SMEs from 2015 to 2022. The investigated indicators were the revenue growth rate, return on equity, environmental, social, and governance (ESG) scores, and a measure of sustainable growth. The authors used the dynamic capability theory and regression models to show that such capabilities positively affect the sustainable growth of the studied enterprises.

Gopane (2020) investigated the relationship between digitisation and labour productivity within the BRICS economic block (Brazil, Russia, India, China, and South Africa). The study utilized an econometric framework grounded in the endogenous growth model to analyse the effects of digitalization on labour productivity. The paper emphasized the difficulties in quantifying the digital economy, especially when using traditional economic indicators. Issues include the need for a standard definition of the digital economy, inadequacies in sector classifications, and complexities in capturing the true impact of digitalisation. The findings point out that while digital technology investment positively correlates with labour productivity, more is needed to sustain an overall upward trend in productivity.

Table 11 presents a systematic comparison with related work. As it can be seen, directly comparing the obtained outcomes is challenging given the substantial differences in subjects, analysis periods, research settings, and methodologies (particularly economic sector classifications and digitization measures). Moreover, the existence of common contextual factors is unclear. One notable exception is the overall negative impact of the COVID-19 pandemic on the studied companies. While the pandemic did accelerate digital transformation in some instances, this effect was consistently examined in all related studies, except for the work by Gopane (2020). Another common contextual factor was the positive effect of existing national policies on the studies companies, which certainly helped their digitisation efforts. So, the COVID-19 pandemic and the existing public policies affected the overall performance of companies and introduced considerable uncertainty in the performed analyses.

Table 11. Systematic Comparison to Related Work.

Reference	Subjects	Research Setting	Analysis Period	Research Questions	Research Methods	Main Findings
This work	Companies listed on B3 (Brazilian Stock Market)	Brazil	2015-2023	Do the use of digitization techniques and methods vary across economic sectors? Do different economic sectors maintain distinct digitization levels? Are there correlations between digitization and corporate finance indicators?	1. Collection of administrative records and financial statements of listed companies from online repositories; 2. Text mining references to digitization in financial statements; 3. Structural equation modelling.	1. ERP and AI technologies have significantly contributed to digitisation; 2. The ICT and commerce sectors have been the most digitised; 3. No correlation was found.

Reference	**Subjects**	**Research Setting**	**Analysis Period**	**Research Questions**	**Research Methods**	**Main Findings**
CETIC.BR (2023)	Companies with ten or more occupied personnel	Brazil	Each other year since 2005	What proportion of industrial companies have digitized their processes (among other questions)?	1. Stratified randomised sampling of studied companies; 2. Descriptive statistics.	51% of the Brazilian industrial companies had already digitised their processes in 2023.
Ren et al. (2023)	Listed manufac-turing companies	China	2009-2020	What is the impact of digitization on the performance of the studied companies?	1. Collection of financial statements from a website and databases; 2. Text mining references to digitization in financial statements; 3. Descriptive statistics and linear regression.	Digitization improves the performance of manufacturing companies.
Zhao and yan Liu (2024)	Manufacturing SMEs	China	2019-2020	What is the direct effect of ICTs on digital integration capabilities and on financial performance?	1. Randomised stratified sampling of studied companies; 2. Collection of standardised data using the Likert scale; 3. Structural equation modelling;	1. Digitization technologies positively affect supply chain integration; 2. Government support generates perceived antagonistic effects on industry.
Sun et al. (2024)	Listed SMEs	China	2015-2020	Does digitization affect the sustainable growth of the studied companies?	1. Collection of administrative records of companies listed on the stock market; 2. Dynamic capability theory; 3. Correlational and multiple regression analyses.	Revenue growth and return on equity are positively affected, particularly in small, non-state-owned, innovative manufacturing firms.
Gopane (2020)	National economies	BRICS countries	1990-2018	Is there a relationship between digitization and labour productivity?	1. Data collection using online databases; 2. Exogenous growth model; 3. Ordinary least squares with robust standard errors.	Digital technology investment positively correlates with labour productivity.

Source: Table created by the author.

Concerning the related work with similar methodologies, the study by Campanelli et al. (2017) focused on identifying and assessing success factors for agile transformation in organisations. The authors proposed an assessment tool to evaluate each organisation's status of agile transformation factors. The investigated success factors were categorised into six groups: customers, management, organisation, processes, teams and tools. The Rasch algorithm was applied to rank these factors. This method was validated through a single-company case study. The study concluded that implementing measurement models, championships, new mindsets, management style changes, and decentralised decision-making is challenging. Conversely, factors such as customer involvement, self-organised teams and cultural changes are relatively more straightforward to implement. Although it provided a structured approach to assessing and prioritising success factors, the study focused on specific organisations rather than economic sectors and digitisation in general.

The methodology used in the conducted studies also resembles those of Naji et al. (2024) and Sousa and Rocha (2019). The first authors develop a model for assessing building readiness for digital transformation in the pre-construction phase. The model employed SEM to assess how construction projects incorporate emerging technologies for improved sustainability and operational efficiency. The model identified 30 key performance indicators categorised into four primary constructs (Technology, Policy, Design, and Management) from expert interviews, literature reviews, and surveys conducted with 13 experts and 300 professionals from various fields. The authors stressed the need to integrate advanced technologies, such as Building Information Modelling (BIM), AI, 3D Printing, AR, VR and IoT, highlighting how these technologies streamline processes, enhance decision-making, and improve project planning, monitoring, and communication. They also emphasised the importance of policy frameworks and design methods to push for adopting digital tools in construction. Their model showed that technology strongly influences digital transformation readiness, followed closely by policy, design, and management. The authors concluded that defining an index to rate performance outcomes is helpful, in their case capturing the readiness for digital transformation. Sousa and Rocha (2019) explored how digital learning can enhance skills crucial for organisations' digital transformation. Their paper combined a literature review with an online survey to gather data on individuals' perceptions regarding the skills needed for digital transformation. The survey via LinkedIn included responses from 127 individuals, which were analysed using SEM. Their study highlighted the importance of developing skills in artificial intelligence and the Internet of Things since they are critical for digitisation.

5.2. Threats to Validity

Construct Validity

Although all analysed data had a single source (i.e., CVM), they complied with standardised definitions and were provided by the investigated companies at different times. This indirect data collection procedure was cost-effective in the conducted studies while reducing the possibility of common factor biases.

The adopted structural equation modelling (SEM) technique used latent variables to represent constructs that were not directly observed but were elicited while the study was conducted. In the present case, the constructs were formulated based on theoretical (i.e. technical or financial) definitions, ensuring their well-definedness.

Internal Validity

Concerning data collection, the adopted convenience sampling method and the study sample size must be analysed. While randomised stratified sampling is the golden standard in business surveys, it faces challenges regarding company availability and cost-effectiveness. On the other hand, with the present study's resources and time constraints, convenience sampling was a reasonable decision. Contrasting the findings presented herein with those obtained in recurrent digitisation surveys (CETIC.BR, 2023) will certainly contribute to developing a more extensive view of the studied reality. In addition, since the adopted sample was small, it was impossible to perform SEM model splitting and cross-validation randomly. This issue slightly undermines the reliability of the reported findings and should be addressed in future research with larger sample sizes.

The theoretical definitions of the investigated constructs were exhaustively studied, leading to an extensive set of variable and relationship definitions. In their analyses, the respective model goodness-of-fit and measurement estimates were verified, as was the robustness of the respective findings. These procedures reinforced the internal validity of the reported findings.

The ICT sector needs to be examined more carefully because some companies in this sector are both technology providers and subject to digitisation, a potential confounding factor. Indeed, it was noted in the analysed sample that ICT companies have been precursors of digitisation, generally implementing internal transformation efforts ahead of other economic sectors as a qualifying strategy to serve their market better. So, despite their dual role, ICT companies have doubly benefited from digitisation, both their own and their customers, deserving to be analysed on par with companies of other sectors. Nevertheless, the size of this double effect on ICT companies has yet to be quantified.

The existence of specific government strategies, plans and policies must also be analysed, as they may also confound the determination of study findings. In the Brazilian case, the federal government formulated a national digitisation strategy in consultation with academic and industrial partners. A document consolidating all the respective plans, procedures, and policies was formulated to guide the Brazilian society's digitisation efforts (MCTI, 2018). In practical terms, the strategy fosters and funds specific actions and projects which might not have been implemented otherwise. Consequently, even though evaluating the effects of these efforts has yet to be developed, the existing strategy has accelerated the overall pace of digitisation in Brazil, not affecting specific companies or economic sectors in specific ways.

External Validity

While general statistical methods were applied herein, all conclusions in this paper pertain only to the Brazilian economy and the sample studied and thus cannot be directly generalised. Such a generalisation would require collecting and analysing substantially more data, ideally obtained from applying a randomised sampling technique in many different parts of the world. Despite this, the Brazilian economy is large and diversified, serving as an adequate location for the studies conducted.

In turn, the methodology adopted in this study can be applied to various contexts, allowing for the generalization of the reported findings. Specifically, non-profit organizations that engage in business transactions can also be analysed using this method. However, there are challenges associated with systematically obtaining and analysing their annual reports, especially since their accounting practices may differ from those of private companies. Nonetheless, these organizations play crucial roles in some local innovation ecosystems. They can serve as both suppliers and adopters of digitization technologies and methods, which warrants further investigation in the future.

6. Concluding Remarks

This paper investigated the conjectures that the use of digitisation technologies and methods varies across economic sectors and that different economic sectors maintain distinct digital transformation levels, delving into correlations between the intensity of digital transformation and the improvement of key financial performance indicators. These hypotheses were investigated using an automated research framework to identify key factors contributing to the success of digital transformation initiatives within business organisations. The developed framework is replicable and extensible in that the set of investigated companies, digitisation technologies and methods, economic sectors and time frames can be modified or amplified to support additional investigations. Consequently, this framework can benefit research and practice, providing coherent analytical and forward-looking approaches for decision-makers and policymakers.

The proposed framework provided statistically significant evidence that economic sectors and the use of contemporary technologies and methods are strong predictors of digitisation. This framework pointed out that using ERP and AI software has been significant and instrumental in digital transformation. The ICT and commerce sectors are notably more advanced in their digitization levels than other economic sectors. However, this study could not significantly establish the impact of digitization efforts on corporate finance despite its general acceptance reported on previous studies conducted in different contexts and periods (Ren et al., 2023; Sun et al., 2024). This outcome points out that contextual factors may affect each analysis, warranting further investigation and replication in the future.

Future work should employ an expanded and refined methodology to investigate factors beyond technical and financial aspects, such as workforce adaption, organizational culture and responsiveness, leadership, high-level commitment and decision processes. These elements and other organizational and cultural factors have been shown to be relevant in the context of digitisation Campanelli et al. (2017). Additionally, future studies should examine the economic connection between digital transformation and labour productivity (cf. Gopane (2020)). This aspect could not be addressed in the present investigation due to a limitation in CVM datasets, which lack information on the employed personnel in each company. Another promising topic for future research is the link between digital transformation and innovation (cf. Frank et al. (2019)), particularly, the interaction patterns that emerge when these processes occur simultaneously.

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