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DIGITALISATION AND FIRM PERFORMANCE DURING THE COVID-19 CRISIS

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Abstract

The purpose of this article is to (1) examine the relationship between digitalisation and different levels or COVID-19 impact and to (2) examine the impact of different levels of degree of digitalisation on firm's performance during COVID-19 pandemic. This paper provides valuable data on the degree of digitalisation to policy makers who have been advocating for and promoting digitalisation initiatives. This study investigates active firms with data extracted from CRSP/Compustat Merged database between 2017-2022, where Covid pandemic refers to 2020-2022. Three different regression models are computed to draw conclusions on how different levels of Covid impact affects the digitalisation (Model 1) and how different levels of degree of digitalisation impacts performance during pandemic (Model 2). The results of Model 1 indicate strong and significant relationship of the different levels of COVID-19 and provide empirical evidence that firms with higher COVID-19 impact were more likely to invest in digitalisation compared to those firms with lower impact. The results of Model 2 indicate a strong and significant relationship for firms with a higher level of digitalisation and firm performance, but these results are opposite during pandemic years. A negative and significant relationship is reported for firms with higher level of digitalisation during COVID-19 years. The results of Model 2 call for further research in this field to understand the underlying factors for such a relation and whether it is explained by the inability to undergo a full and complex digital transformation, the increased financial constraints because of Covid-19 pandemic and lastly, a possible lag effect, where the benefits of digitalisation may not be immediately reflected in ROA. This study emphasizes the importance of considering the specific context and stages of digital transformation when analysing the impact of digitalisation and firm outcomes during COVID-19 pandemic.

Key Words: Digitalisation, firm performance, COVID-19 pandemic, shock crisis.

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1. Introduction

Digitalisation is multi-faceted. It involves the use and applications of a broad range of technologies, for different purposes. It aims to transform the business models and processes, strategy, and organisational structures. It is not purely transitioning the existing processes to a digital platform or simply investing in technology. It is about creative, innovative and utilise the digital tools to its max capacity to secure long-term growth and to gain a competitive advantage.

The COVID-19 pandemic has caused a Shock Crisis worldwide, leading to negative impacts on businesses' productivity with long-lasting effects. Additionally, the measures implemented to control the spread of the virus have greatly influenced how companies engage with digital technologies. (Abidi, El-Herradi, & Sakha, 2022) (Apedo-Amah, et al., 2020). Organisations had to become creative and innovative. Adapting their business models via digital systems was no longer to gain a competitive advantage, but a necessity to survive and provide business continuity remotely, during lockdowns & social distancing restrictions.

Most studies emphasize that traditional policy response is irrelevant for COVID-19 crisis and highlight the need for further research to collect empirical evidence and develop new frameworks and theories. (Busato, Chiarini, Cisco, & Ferrara, 2021) (Estrada, Koutronas, & Lee, 2021) This highlights the reason why businesses and policymakers started to explore how digitalisation could contribute to recover from this crisis and respond to future crises. The lockdown and other measures against COVID-19 accelerated the digital transformation with long lasting and irreversible effects.

Since the beginning of the COVID-19 pandemic, there's been a sharp increase in the digital uptake in SMEs. The business environment is rapidly changing and "Up to 70% of SMEs are making more use of digital technologies due to COVID-19" (OECD, 2021). The current drive and aspiration for digital transformation creates uncertainty and need for research in various fields such as internal auditing (Betti & Sarens, 2020), employment (Benedetti, Sedláček, & Sterk, 2020), productivity (Bloom, Bunn, Mizen, Smietanka, & Thwaites, 2020), business models (Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020), company law (ICLEG, 2016), political regulation (Schmiedchen, Kratzer, Link, & Stapf-Finé, 2022), firm resilience and performance (Teruel, et al., 2022)

COVID-19 pandemic did not only accelerate the speed of digitalisation, but also proved that there is no alternative to the current technology path. (Schmiedchen, Kratzer, Link, & Stapf-Finé, 2022). "It is unlikely that economies and societies will return to "pre-COVID" patterns; the crisis has vividly demonstrated the potential of digital technologies and some changes may now be too deep to reverse" (Abidi, El-Herradi, & Sakha, 2022)

Betti et al. (2021) provides evidence that digitalisation is changing the working practices of internal auditors. They argue that data analytics is a powerful tool to improve the accuracy of audit activities. Teruel et al. (2022) provides evidence that the negative impact on employment was stronger in the less productive firms. They argue that increase in digitalisation provides resilience to organisation in times of crisis and that the COVID-19 pandemic widened the gap in terms of degree of digitalisation across firms. (Teruel, et al., 2022). Abidi et al. (2022) also provides evidence that digitalisation can play an important role in mitigating the impact of the crisis. They further argue that policy makers should further accelerate the digital transformation and minimise the digital gap across firms.

There is vast literature on digitalisation, how to approach it and how to make it successful. However, in times of Crisis, firms were not able to follow all the phases of digitalisation. They had to act fast and adapt fast, make rushed decisions to remain in business. Thus, the increase in digitalisation as a result of COVID-19 pandemic is not representative whether this allowed the organisation to overcome the crisis and also increase the profitability. Little evidence is provided on what the impact of digitalisation is on firm performance during COVID-19 pandemic and what is the relationship between digitalisation and the different levels of COVID impact.

Betti et al. (2021) highlights the need to further investigate how COVID-19 pandemic impacts the level of digitalisation of organisations and the use of new technology by Internal Auditors. Teruel et al. (2022) highlights the need for further analysis of the persistence of the technological digital gap, its underlying factors, and its effects on firm performance. Gurumurthy et.al. (2020) investigated the digital maturity and firm performance however, this was not during pandemic times of forced transformation where businesses didn’t have the luxury to follow extensive frameworks.

Thus, this paper provides answers to two main questions. First, what is the relationship between digitalisation and different levels of COVID-19 impact. Second, what is the impact of digitalisation on firm’s performance during COVID-19 pandemic.

This study contributes to the existing literature by providing empirical evidence on various aspects related to digitalisation and its impact on firms’ performance during the COVID-19 crisis.

Firstly, it explores how different levels of COVID-19 impact (High, Medium, Low) influence the extent of digitalisation in firms. Secondly, it investigates whether there exists a positive relationship between a firm's profitability and the degree of digitalisation (High, Medium, Low). Additionally, it examines whether the relationship between a firm's profitability and the degree of digitalisation is different during COVID years. And lastly, it provides valuable data on the degree of digitalisation to policy makers who have been advocating for and promoting digitalisation initiatives.

This study investigates active firms with data extracted from CRSP/Compustat Merged database between 2017-2022, where Covid pandemic refers to 2020-2022. Three different regression models are computed to draw conclusions on how different levels of Covid impact affects the digitalisation (Model 1) and how different levels of degree of digitalisation impacts performance during pandemic (Model 2).

The results of Model 1 provide empirical evidence for the first hypothesis and conclude that firms highly affected by COVID-19 are more likely to invest in digitalisation. These support the theoretical framework of Verhoef, et.al. (2021) and Gurumurthy, et.al. (2020)

which says that digitalisations enables businesses to be creative and think of longer-term growth strategies. Furthermore, the results complement other studies which concluded that firms are increasingly relying on digital solutions to respond to COVID-19 crisis (Apedo-Amah, et al., 2020; Abidi et al. 2022). To further test the first hypothesis, an additional regression analysis using the overall COVID impact index was conducted, and it supported the previous findings, indicating that firms with high Covid impact are more likely to increase their level of digitalisation.

The results of Model 2 do not provide empirical evidence for the second hypothesis. The results do support the prior studies that firms with higher degree of digitalisation are usually more profitable, but this is not valid during pandemic years. Three main factors are identified which could explain this. First, the inability to undergo a full digital transformation which implies a complete change of business model and a long-term digital strategy. Second, the increased financial constraints because of Covid-19 pandemic and lastly, the delayed return on investments. The additional regression analysis using the overall degree of digitalisation index supported the previous findings.

The study is concluded by providing several topics for future research. First, to investigate the persistence of the digital gap and how this impacts the firms' performance. Second, investigate what new and emerging key performance indicators are arising to measure digitalisation and how these reflect the firm's performance. Third, analyse a possible lag effect of firms who heavily invested in digitalisation during crisis times and post-crisis financial benefits. And lastly, analyse the challenges and performance risks of cyber security attacks.

The rest of the paper consists of three sections and concluding remarks. The next section reviews the main theoretical background and prior literature. Section 3 describes the data sample, key variables, descriptive statistics, and the empirical methodology. The empirical tests and results are discussed in Section 4. Section 5 concludes and discusses study limitations by providing some topics for further research.

2. Theoretical Background and Hypotheses Development

2.1 Covid-19 Crisis

In December 2019, Wuham Municipal Health Commission made a statement of the increase in viral pneumonia cases. In January 2020, the Chinese authorities determined that the outbreak is caused by a novel coronavirus. The virus started to spread so fast that within just one month it became an emergency of international concern and at the beginning of February 2020, the UN crisis management policy was activated. In March 2020, the virus was categorised as a pandemic and WHO (World Health Organisation) urged all countries to take urgent and aggressive measures to stop the spread of the pandemic. (WHO, 2022) The whole world was in panic with the number of infections rising as well as the number of deaths rising, and the inability to provide treatment. The world was unprepared to respond to a pandemic of such a global scale, which led to shortage of medical supplies and extremely high pressure on the health, transport, and other industries. It was impossible to provide intensive care and life support to all the infected patients. Thus, governments started to take drastic measures to stop the spread. The whole world entered a lockdown. Everyone started to work from home, there were no more face-to-face outings, and the face-to-face interactions were completely minimised. The global economy was shut down and economists were predicting the biggest shock market crash in the 21st century. (Estrada, Koutronas, & Lee, 2021)

Historically, there were only two similar episodes: the Black Death (1347-1351) and the Spanish Flu (1918-1919). Estrada et.al. (2021) conducted an analysis and formulated an analytical framework on what implications the temporal epidemies have on the financial markets. They introduce the new concept of stagpression, "a new economic phenomenon to explain the uncharted territory the world economies and financial markets are getting into". (Estrada, Koutronas, & Lee, 2021) They explain that volatility shocks affect the economy with a decline in investment, GDP, output, and employment leading to credit market tightening and increased liquidity concerns.

Their results conclude that COVID-19 pandemic has widespread economic disruptions and that the traditional policy responses are irrelevant because the economy's sustainability threshold level is crossed. They argue that COVID-19 generated an unacceptable economic environment given the business bankruptcies, foreclosures, and restraint access to debt and it might take no led than one year to recover from this shock. They call for further analysis and research using real data from economies and case studies to ensure framework validity. (Estrada, Koutronas, & Lee, 2021)

Yarovaya et. al (2022) evaluate the COVID-19 pandemic impact on four broad classes of financial assets: equity indexes, precious metals, 10-year benchmark bonds and cryptocurrencies. (Yarovaya, Matkovskyy, & Jalan, 2022) They conclude that the pandemic has affected the financial markets across all dimensions including the contemporary assets such as cryptocurrencies. They explain that the pandemic is the first macroeconomic shock for the cryptocurrency market, and they apply the term of "Black Swan" to describe this effect. Their results demonstrate different recovery patterns for each financial asset with cryptocurrency being the riskier class of investment.

Busato et.al. (2021) explain how the temporary lockdown policies amplifies the recession’s severity. It is explained that the lockdown policy significantly affected the labour market, decreased the GDP which is associated with decrease in household consumption, decrease in productivity and other severe adverse macroeconomic effects. They highlight that policymaker experienced a severe trade-off between preventing deaths from COVID-19 and GDP slowdown. Furthermore, they argue that the economy starts recovery once the lockdowns are lifted. Using a DSGE model, they conclude that the pre-COVID-19 conditions are reached only after two years. They also emphasize that the recovery phase for the investments could be more lasting. (Busato, Chiarini, Cisco, & Ferrara, 2021)

Shen et.al. (2020) conducted a regression analysis using DID approach and provided empirical evidence that COVID-19 pandemic had a negative impact on corporate performance. Firms with lower revenues and lower scale of investment had a more significant impact on their performance because of the pandemic. They emphasize that the negative impact is stronger in the highly impacted areas and industries. It is concluded that COVID-19 pandemic reduced firm’s revenue leading to lower performance. It is implied that firms with higher level of investment and income will reduce the negative pandemic impact. (Shen, Fu, Pan, Yu, & Chen, 2020)

Khan et.al. (2022) did similar research by examining whether financing constraints had an impact on how SMEs responded to the COVID-19 crisis. They argue that COVID-19 pandemic has some similarities with the 2008-09 crisis as both had a significant global impact on corporate bankruptcies, losses, and liquidity shortages. However, the pandemic represents a demand and supply shock for both lenders and borrowers. It was concluded that financially constrained SMEs were overdue in meeting their obligations to financial institutions and were more likely to experience liquidity and cash flow problems.(Khan, 2022)

To conclude, the COVID-19 pandemic is classified by most studies and literature as a shock crisis. It is compared to other economic crisis and epidemic crisis, yet different to the extend it affected supply and demand, lenders, and borrowers. Most studies emphasize that traditional policy response is irrelevant for COVID-19 crisis and highlight the need for further research to collect empirical evidence and develop new frameworks and theories. This highlights the reason why businesses and policymakers started to explore how digitalisation could contribute to recover from this crisis and respond to future crises. The lockdown and other measures against COVID-19 accelerated the digital transformation with long lasting and irreversible effects.

2.2 Digitalisation and Covid-19 Crisis

Digitalisation refers to the process of integrating digital technologies in all aspects of social, economic, and political life. It involves the utilization of digital tools, systems, and processes to transform and enhance traditional analogue practices. Digitalisation creates opportunities for innovative business models. Data is the foundation of digitalisation which combines the traditional automated data processing and the emerging data techniques likes machine learning, big data, and artificial intelligence. (Schmiedchen, Kratzer, Link, & Stapf-Finé, 2022), (Riedl, Benlian, Hess, Stelzer, & Sikora, 2017), (Legner, et al., 2017)

Digitalisation aims to provide more efficient coordination between processes, to enable data-driven insights, and enhance user experiences. (Verhoef, et al., 2021) It is not about turning the current processes into digital versions but rethinking the existing model from new opportunities brought by digital technologies. (Parviainen, et.al. 2017)

Digitalisation is not a new phenomenon. Across sectors, firms of all sizes are increasingly making use of digital tools and search of new ways to gain a competitive advantage. Some smaller firms are slower in undergoing a digital transformation whilst other sectors are faster in responding to market needs. (OECD, 2021) The World Economic Forum, defined the pre COVID-19 pandemic industrial stage as "a Fourth technological revolution". (Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020) However, the COVID-19 crisis has enhanced the importance of digitalisation. It forced most organisations to implement smart working solutions to survive this Shock Crisis and remain in business during lockdowns and social distancing restrictions. "Up to 70% of SMEs are making more use of digital technologies due to COVID-19" and most of these changes are predicted to last. (OECD, 2021) (Abidi, El-Herradi, & Sakha, 2022) Firms are increasingly relying on digital solutions to respond to COVID-19 crisis (Apedo-Amah, et al., 2020) and Abidi et al. (2022) provides evidence that the digitalisation acted as a hedge during the pandemic. The authors argue that digitalisation plays an important role in building resilience against a shock crisis such as COVID-19 pandemic.

Verhoef et.al. (2021) provide a discussion and explain the flow model of digital transformation by addressing the "External factors that drive digital transformation", the "Phases of Digital Transformation", and the "Strategic Imperatives for Digital Transformation". Appendix A provides the detailed flow model. They identified three main reasons to undergo a digital transformation. First, the wide entrance of new digital technologies pushes firms to transform their business digitally. Second, businesses must adjust to respond to increased global competition and tougher competition against young digital firms. And third, customers behaviour and needs are changing. Consumers are more digitally engaged, and businesses need to adapt to keep their customers satisfied.

This framework supports the findings of Abidi et al. (2022) and Apedo-Amah et.al. (2020) that digitalisation provides a buffer against a shock crisis. COVID-19 pandemic was the "external factor" to push companies in using the new digital technologies, new communication & remote working platforms, invest in E-commerce and completely re-think the business models to meet customer's needs and have business continuity. Gupta et.al.

(2020) provide an organizing framework on how digital analytics can be used by firms to generate consumer insights. In addition to the external factors identified by Verhoef et.al. (2021) they also argue that “Data Privacy and Security” is yet another factor why firms opt for the new-age technology. This reduces the risk of security breaches which could ultimately make the customer data vulnerable. They further argue that the new-age technology could not only be used to meet the “new” digital needs of the customers, but to also influence customer behaviour during the purchase stage. Appendix B provides the model of Tackling Digital Transformation.

Gurumurthy et.al. (2020) argue that “digital transformation is about both doing old things better, faster, and cheaper and doing new things that weren’t possible before”. They argue that costs savings are not the ultimate goal of investing in digitalisation. The ultimate aim is to boost growth, improve customer satisfaction and product quality and contribute to better financial performance**.** The COVID-19 pandemic has demonstrated how creative and inovative businesses can be by itroducing new products/services and completely re-designing their business models to accommodate the new norms of operating remotely and contactless. This emphasisez that firms were not opting for digitalisation to cut costs, but to remain in business, to generate sales while accounting for the increase in costs driven by inflation. The goal was to retain the customer base and re-think the long-term recovery strategy.

Apedo-Amah et.al. (2020) conducted a comprehensive assessment using a survey of what the short-term impact of COVID-19 pandemic had on businesses worldwide with a focus on developing countries. They conclude that the COVID-19 crisis severely affected the firms “often through multiple shocks at the same time”. They observe that firms face significant uncertainties about the future, report serious drop in sales and have reduced access to finance.

Benedetti Fasil et.a. (2020) provide an empirical tool (EU start-up calculator) to allow researches and policy makers to estimate the medium impact that COVID-19 pandemic may have on employment due to distruption in start-ups and young firms. This study provides further empirical evidence to Apedo-Amah et.al. (2020) survey by explaining what companies might be more susceptible for bankruptcy and might have a more challenging path to recovery because of the COVID-19 shock. They argue that the young firms who are in a “more fragile stage of their firm life-cycle are being more susceptible to disruption of supply chains, a drop in demand for their products or services, limited access to funding and more stringent regulations” (Benedetti Fasil, Sedláček, & Sterk, 2020)

Troise et.al. (2022) conducted an online survey targeting Italian SMEs to examine the role of agility in the digital transformation era and VUCA environment. VUCA environment stands for Volatile-Uncertain-Complex-Ambiguous environment. It is explained that SMEs are more vulnerable in the “hypercompetitive” environment. The authors analyse the business agility by addressing five main capabilities, including a capability for digital technology. It is concluded that higher agility leads to better performance and that agility is highly dependent on digital technology. It is argued that innovation and relational capability might be the key for SMEs in VUCA environments. (Troise, Corvello, Ghobadian, & O'Regan, 2022)

Thus, complemeting the prior studies and results, this paper aims to provide empirical testing on how different levels of Covid impact (High, Medium and Low) impact the firm's degree of digitalisation. It is interesting to understand whether firms' digital investment strategy was driven by the degree of COVID-19 impact. Following the theoretical framework described by Verhoef et.al. (2021), Gupta et.al. (2020) and Gurumurthy et.al. (2020), I expect that the firms with higher pandemic impact had a higher urge to invest in digitalisation. These organisations had no choice but to adapt and respond to external factors which drive the digital investment. Since I expect a strong positive relationship between the higher COVID-19 impact and the degree of digitalisation, the following hypothesis is formulated:

H1: *Firms with higher COVID-19 impact have a higher need to invest in digitalisation.*

2.3 The Degree of Digitalisation and Firm Performance

Digitalisation is a rising trend, but simply investing in technology in not enough for a successful digital transformation. The Verhoef et.al. (2021) explains three main steps in digital transformation, which are Digitisation, Digitalisation and Digital Transformation. First, the firms must undergo an automation of processes and tasks (digitisation). Followed, by introduction of digital distribution and communication channels (digitalisation). And lastly, the introduction of new business models and digital platforms (digital transformation). They explain the "Strategic imperatives" to fulfil the digital transformation's potential. The digital resources, organisational structure, growth strategy, metrics and goals are the foundations of realizing the full potential of the digital transformation. New key performance indicators linked to digitalisation must be introduced to monitor and fine-tune the business model in addition to the traditional performance indicators.

Multiple studies agree that effective digital strategy is more likely to bring competitive advantage and means to increase profit margins (Kane, Palmer, Philips, & Kiron, 2015); (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011); (Tschakert, Kokina, Kozlowski, & Vasarhelyi, 2016); (Legner, et al., 2017) (Verhoef, et al., 2021).

Kane et.al. (2015) performed a survey and asked respondents to rank the digital maturity of their organisations against an ideal organisation which successfully completed a digital transformation. Their findings suggest that effective digital strategy is more strongly associated with digital maturity than technology use. Their findings highlight that the extent to which the technology is used was the main differentiating factor between high and low digital maturity companies. The success will depend on the ability to implement creatively the new-age technology by rethinking strategy, culture, and talent.

LaValle et.al. (2011) by using a survey concluded that top performers were twice as likely to use data analytics to guide future strategies and day-to-day operations than low performers. For the data analytics to exhaust its' full potential it must be linked to business strategy, impended in the business processes and customer friendly so that actions could be taken at the right time. They suggest that new tools can make the data easier to understand and enable business to act fast. Their results highlight the positive relationship between using technology to understand the data and being a high performing firm. This emphasizes that firm with higher degree of digitalisation lead to better performance.

Parviainen, et.al. (2017) is defining a theoretical model to tackle the digital transformations using four steps: defining the digitalisation goals, reviewing the current state, identifying the roadmap to digitalisation, and implementing the transformation with technical support. Appendix E provides the model for tackling the digital transformation.

Gurumurthy et.al. (2020) provide seven digital pivots to explain how and why digital maturity is associated with better financial performance.Appendix C provides the theoretical framework and Appendix D provide examples of best practices of the seven digital pivots. They conducted a survey by asking their respondents to provide the degree “to which they saw a positive business impact from the application of that pivot within their organization”. They agrregated these results to classify the firms between high, medium and low digital maturity. Their results suggests that building the pivot capabilities bring a high range of business benefits. More specifically, the higher maturity companies reported receiving benefits from every digital pivot. A possible reason for lower maturity companies for missing out on growth opportunities is not using the digitally enabled business models. Their results support the theoretical framework described above which says that in order to be successful, the firm must undergo all the digital transformation stages which involves the inroduction of new business models and long-term digital startegies. (Verhoef, et al., 2021) (Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020) (Kane, Palmer, Philips, & Kiron, 2015) (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011)

Betti et.al. (2020) use a qualitative research methodology to provide insight on how the internal auditing function is evolving during the increasingly digitalised business environment. They explain two main constraints that firms face with digitalisation. First, is the time required to implement the digital analytics and second, the costs involved. They argue that it is costly to implement digital transformation and the skills required to use such technologies, which makes it worth analysing how the increased digitalisation investments affects firm’s performance (Betti & Sarens, 2020)

To overcome these challenges, the research from McKinsey list four ways that AI can improve efficiency and create value. These are the following: 1. project enlightened R&D, real-time forecasting, and smart sourcing; 2. higher productivity, lower cost, and better efficiency of operations; 3. promotion of products and services at the right price, with the right message, and to the right targets; and 4. providing enriched, tailored, and convenient user experience. (Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020) This exemplifies that with the right approach and strategy, the digital transformation could be a game changer.

Prior studies suggest that digitalisation can provide resilience when firms are hit by an economic shock. Abidi, et.al. (2022); Teruel, et al. (2022) and Gurumurthy et.al. (2020) indeed concluded that higher digital maturity firms have better financial performance. Shen et.al. (2020) concluded the negative impact that COVID 19 pandemic had on financial performance. However, the impact of digitalisation on firm’s performance during Covid-19 pandemic was not empirically tested. Thus, to provide empirical evidence whether there is a positive relationship between firm's profitability and the degree of digitalisation during COVID-19 crisis, the following hypothesis is formulated:

H2: *Firms with higher degree of digitalisation are more profitable during the COVID-19 Crisis.*

3. Research Design

3.1 Database and Data Sample

This study investigates all active firms extracted from CRSP/Compustat Merged database using WRDS online database. The CRSP/Compustat Merged (CCM) database is a comprehensive financial dataset that combines the stock price and return data from CRSP with all the other financial and fundamental data on publicly traded companies from Compustat. The aim of this paper is to investigate the digitalisation and firm performance during COVID-19 pandemic. Thus, a wide range of variables are used to define the firm performance, digitalisation, the pandemic impact whilst controlling for other factors such as the firm size, and the number of employees. The CRSP/Compustat Merged database was a perfect fit to extract all this information and facilitate the empirical analysis.

Prior studies provide analysis and evidence from countries across EU and UK (Teruel, et al., 2022) (Betti & Sarens, 2021), using data from surveys (Gurumurthy, Schatsky, & Camhi, 2020), (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011), (Kane, Palmer, Philips, & Kiron, 2015), (Abidi, El-Herradi, & Sakha, 2022), qualitative research approaches (Betti & Sarens, 2020), case studies and discussions (Verhoef, et al., 2021), (Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020) amongst others. Therefore, this study is contributing to existing literature by providing new empirical evidence using a quantitative research approach. It provides a new perspective on digitalisation and firm performance in global markets. The time frame between 2017-2022 is used, where Covid pandemic refers to 2020-2022. This time frame provides the firm performance pre and during pandemic to calculate and analyse the COVID-19 impact. According to WHO, World Health Organisation, no significant covid restrictions were imposed as of Q3 2022 (WHO, 2022). Furthermore, Estrada et.al. (2021) is predicting that companies will need at least one year to recover from the pandemic and return to its pre-pandemic levels, whereas Busato et.al. (2021) predict that only after two years a firm might return to pre-pandemic conditions. Consequently, there is not sufficient data to analyse the post pandemic recovery and the longer-term impact that digitalisation has on performance.

The raw data consisted of 33,082 observations and 7,508 firms. After removing all the inactive firms and firms with missing data, the sample consisted of 16,313 observations and 2,838 firms. Most observations were lost due to deletion of inactive firms (3,881 observations), due to incomplete data on Working Capital (4,101 observations) and incomplete data on other variables (4,069 observations). Further observations were lost due to incomplete data for years 2019 & 2020 and inability to calculate the COVID impact (4,195).

The data was analysed across 45 countries, however firms from Unites States formed 79% of the sample. Table 1 provides the details of sample selection and Table 2 provides the description of firm-year observations by country.

The remainder of this section will explain the variables and the regression equations to empirically test the formulated hypotheses.

TABLE 1: Sample Selection

	N	
Sampling Procedure	Observations	Firms
Initial Observations derived from CRSP/Compustat Merged Database	**33,082**	**7,508**
Less: Inactive Firms	3,881	1,490
Less: Missing information on the main below variables:	4,069	643
Income Before Extraordinary Items - Available for Common		
Total Assets		
Capital Expenditure		
Depreciation and Amortization		
EBITA		
Total Liabilities		
Less: Working Capital	4,101	768
Less: No. Employees	498	80
Less: Outliers after calculating the PCA Index for Covid Impact and Degree of Digitalisation	25	5
Less: Observations with no Covid Impact	4,195	1,684
Final Sample for the Regression Analysis	**16,313**	**2,838**

Table 1 *– Sample Selection*

TABLE 2: Description of the Firm-Year Observations in the Models

Country	*Freq.*	*Percent*	*Cum.*
Antigua and Barbuda	6	0.04	0.04
Argentina	53	0.32	0.36
Australia	41	0.25	0.61
Belgium	22	0.13	0.75
Bermuda	139	0.85	1.60
Brazil	74	0.45	2.05
British Virgin Islands	160	0.98	3.03
Canada	653	4.00	7.04
Cayman Islands	706	4.33	11.37
China	49	0.30	11.67
Colombia	6	0.04	11.70
Curaçao	6	0.04	11.74
Cyprus	6	0.04	11.78
Denmark	10	0.06	11.84
Finland	6	0.04	11.87
France	60	0.37	12.24
Germany	40	0.25	12.49
Guernsey	6	0.04	12.52
Hong Kong	18	0.11	12.63
India	28	0.17	12.81
Ireland	171	1.05	13.85
Israel	315	1.93	15.78
Italy	16	0.10	15.88
Japan	60	0.37	16.25
Jersey	43	0.26	16.51
Liberia	6	0.04	16.55
Luxembourg	67	0.41	16.96
Marshall Islands	112	0.69	17.65
Mauritius	11	0.07	17.72
Mexico	70	0.43	18.15
Netherlands	70	0.43	18.57
Norway	6	0.04	18.61
Panama	12	0.07	18.68
Peru	18	0.11	18.79
Philippines	6	0.04	18.83
Russia	14	0.09	18.92
Singapore	23	0.14	19.06
South Africa	48	0.29	19.35
South Korea	36	0.22	19.57
Spain	6	0.04	19.61
Sweden	10	0.06	19.67
Switzerland	52	0.32	19.99
Taiwan	30	0.18	20.17
United Kingdom	184	1.13	21.30
United States	12,838	78.70	100.00
Total	**16,313**	**100.00**	

Table 2 *- Description of the Firm-Year Observations in the Models*

3.2 Construction of the Models

3.2.1. Model 1: The Relationship between Digitalisation and Different Levels of COVID-19 Impact

The first hypothesis aims to draw conclusions of whether the firms with higher COVID-19 impact were more prone to invest in digitalisation. The equation to test H1 is the following:

$$Intangible_{Assets} = \beta 0 + \beta 1 * COVID_{Impact} + \beta 2 * Revenue_{Growth_{Dummy}} + \beta 3 * ROA + \beta 4 * Firm_{Size} + \beta 5 * Firm_{Age} + \gamma Industry + \delta Year + \varepsilon$$

In this equation, the Intangible_Assets is the dependent variable and COVID_Impact is the independent variable, followed by mutliple control variables and fixed effects for industry and year, which will be described below.

The Intangible_Assets measure the digitalisation following the same approach as prior similar studies. (Betti & Sarens, 2021); (Teruel, et al., 2022). Teruel et.al (2022) identified that an important dimension in the study was the investment in intangible assets. It was concluded that inovation profile, investment in software and training are positevely related to expected long term digitalisation. Thus, in this regression equation, I expect that most of the degree of digitalisation will be explained by the intangible assets variable which was measured as % of total assets.

Shen et.al. (2020) and Khan (2022), amongst other studies reviewed in previous section, concluded that COVID-19 pandemic had a negative impact on firm performance, it's liquidity and restraint access to debt. Betti et.al. (2021) use an interesting approach in their study on effects of digitalisation on internal audit activities and practices. They used the principal component analysis (PCA) to group four different survey questions under one index. Abidi et.al.(2022) use the same approach to transform the digital connectivity variables into an index. I followed the same approach and grouped three main variables to calculate the *COVID_Impact_Index.*

The principal component analysis (PCA) is a statistical technique that selectively reduces the dimensionality of data while maintaining maximum variance. To achieve this, principal components should be generated. The principal component is a new set of variables containing a linear combination or the original values. (Janićijević, Mizdraković, & Kljajić, 2022) The number of principal components created depends on the number of variables included in the model. A very small number of components is sufficient to cope with data variability and reduces the complexity of the analysis. The PCA analysis is extremely useful to identify the impact on grouped impact factors. (Janićijević, Mizdraković, & Kljajić, 2022) Hence, PCA is an appropriate model to use for analysing the different levels of COVID-19 impacts. The *COVID_Impact_Index* is the PCA index to assess the Shock Impact of the pandemic on firms in the selected sample.

The principal component analysis index (*COVID_Impact_Index*) was computed using STATA. To calculate the index, the change % between 2020 vs 2019 years for the following variables were used: *No. Employees, Leverage and Liquidity.* The below formula was used to calculate the change % for each variable and each firm.

$$Change\ \%\ of\ X = (X_{2020} - X_{2019})/X_{2019}$$

Teruel et.al (2022) and Apedo-Amah et.al. (2020) studies concluded that COVID-19 has a significant negatve impact on the number of employees. Thus, derived from prior results, the change % in the number of employees between Covid and pre-Covid year will explain the degree of Covid Impact. Furthermore, Shen et.al. (2020) and Khan et.al. (2022) provide further empirical evidence of the significant negative impact that Covid pandemic had on leverage and liquidity. Thus, driven by their results, I am including these two variables in the PCA model of Covid_Impact_Index. I am following the same formulas as presented by Shen et.al (2020), meaning that Liquidity is measured as Free Cash Flow and Leverage is the ratio of Total Liabilities over Total Assets. The detailed variable definitions are provided in Appendix F.

Calculating the change % between 2020 vs 2019 means that the COVID impact was calculated for one year and 2,838 firms. This rank was then applied to all the years in the sample data. Consequently, this makes *COVID_Impact* variable firm specific and constant across all years. The reason of calculating the impact only between 2020 and 2019 is to observe the actual SHOCK Impact once the firms were hit by pandemic. As explained in the previous section, most studies and literature classify COVID-19 pandemic as Shock Crisis. If I were to include the change for other Covid years (2021 & 2022) to test the first hypothesis, I would’ve captured the impact of responding and/or adapting to a shock crisis. The formulated hypothesis aims to examine the relationship between the level of COVID impact and digitalisation.

Before computing the PCA index, I analysed the correlation of the variables to ensure that variables with high correlation are not included in the model. Even though PCA is designed to tackle the issue of highly correlated variables, excluding the highly correlated variables might help to capture the underlying relationship between variables and lead to more informative principal components. All the three variables included in the Covid Impact PCA Index have a correlation coefficient lower than +/-0.1. Table 3 provides a summary of these results.

As explained by Janićijević et.al. (2022), a very small number of components is sufficient to cope with data variability. Thus, Component 1 (PC1) was used as the final index for COVID_Impact_Index with an eigenvalue of 1.098. PC1 includes the positive magnitude of variables No. Employees and Leverage and the negative magnitude of Liquidity. Table 3 provides a summary of these results.

The *COVID_Impact_Index* was ranked between High, Medium, and Low and three equal groups were formed with 946 firm specific observations per group. Table 3 provides the

Descriptive Statistics of Covid Impact Groups. It is important to highlight, that *COVID_Impact* refers to the negative impact, the Shock of Covid. Thus, the groups with High Covid Impact are the firms which were hit the most by the pandemic and the groups with Low Covid Impact are the firms which were least hit by Covid or experienced growth.

The Principal Component Analysis (PCA) can result in components with negative values even if the original variables do not include negative values. The PCA index will always have a mean close to zero. A negative value means that the values are below the mean of the index and a positive value means that the values are above the mean of the index. (Janićijević, Mizdraković, & Kljajić, 2022) Consequently, a negative value of the Covid Index represents a negative Covid impact, a positive value represents that the impact was very low or firms even experienced growth. As presented in Table 3, the overall Covid index mean is -0.007 with the minimum value of -18.160 and the maximum value of 30.540.

In the above equation, the *COVID_Impact is* classified as a dummy variable where:

1. *COVID_Impact_High* is the group of firms with High Covid Impact with PCA Index values between -18.163 and -0.207. The variable takes value of 1 for High Impact and 0 for otherwise.
2. *COVID_Impact_Medium* is the group of firms with Medium Covid Impact with PCA Index values between -0.206 and -0.005. The variable takes value of 1 for Medium Impact and 0 for otherwise.
3. *COVID_Impact_Low* describe the firms with Low Covid Impact with PCA Index values between -0.004 and 30.545. The variable takes value of 1 for Low Impact and 0 for otherwise.

According to the first formulated hypothesis, the $\beta 1$ coefficient is expected to be positive for the groups with high Covid impact and negative for the groups with low Covid impact.

Like prior studies, further control variables are included to improve the validity and reliability of the observed relationship between the dependent and independent variable such as *Revenue_Growth*, *Firm_Age* (Teruel, et al., 2022), *ROA* and *Firm_Size* (Shen, Fu, Pan, Yu, & Chen, 2020).

Additionally, following Teruel et.al. (2022) and Shen et.al. (2020), Industry and Year fixed effects were included in the regression analysis together with robust standard deviations. Dummy variables have been created for each unique value of Industry and Year, and these dummies are included in the regression to capture industry-specific and year-specific effects on the dependent variable (intangible assets).

Three different regression analyses are run, and results are compared between the three different Covid_Impact Groups to draw conclusions about the first hypothesis if higher COVID Impact leads to higher degree of digitalisation.

TABLE 3: Covid Index PCA

Panel A: Correlation of Variables used for Covid Index PCA

		(1)	(2)	(3)
(1)	*No. Employees*	1.0000		
(2)	*Leverage*	**0.0873***	1.0000	
(3)	*Liquidity*	-0.0004	-0.0438	1.0000

Panel B: Principal Components

Component	*Eigenvalue*	*Difference*	*Percent*	*Cum.*
Comp 1	1.098	0.098	0.366	0.366
Comp 2	1.000	0.097	0.333	0.699
Comp 3	0.902			1.000

Panel C: Principal Components (Eigenvectors)

Variable	*Comp 1*	*Comp 2*	*Comp 3*	*Unexplained*
No. Employees	0.632	0.449	- 0.632	-
Leverage	0.707	0.002	0.708	-
Liquidity	- 0.319	0.894	0.316	-

Panel D: Descriptive Statistics of Covid Impact Groups

Covid Impact Group	*N*	*Mean*	*SD*	*Min*	*Max*
High	946	-0.514	0.667	-18.163	-0.207
Medium	946	-0.114	0.054	-0.206	-0.005
Low	946	0.629	1.475	-0.004	30.545
TOTAL	2,838	-0.007	1.049	-18.160	30.540

Table 3*:*

Panel A: *provides the correlations of variables used for Covid PCA Index.*
Panel B: *provides an overview of the Principal Components.*
Panel C: *provides the eigenvectors of the Principal Components.*
Panel D: *provides the descriptive statistics of Covid Impact Groups.*

Note: *The Covid Index was predicted using PCA component 1 with an eigenvalue of 1.098. The index was then ranked between High, Medium and Low Covid Impact and three equal groups were formed. Covid Impact refers to the negative impact, the Shock of Covid. To assess this shock the change % between 2020 vs 2019 is used. Thus, the groups with High Covid Impact are the firms which were hit the most by Covid and the groups with Low Covid Impact are the firms which were least hit by Covid or experienced growth. Consequently, a negative value of the Covid Index represents a negative Covid impact, a positive value represents that the impact was very low or firms even experienced growth. This shock impact was assigned to all years and used for empirical testing.*

3.2.2. Model 2: The Impact of Degree of Digitalisation on Financial Performance (ROA) during COVID-19 Pandemic

The second hypothesis is testing whether the degree of digitalisation has an impact on firm performance during the COVID-19 pandemic. The equation to test H2 is the following:

$$ROA = \beta 0 + \beta 1 * Degree_{Digitalisation} + \beta 2 * COVID_{years} + \beta 3 * DD\_COVID_{Interaction} + \beta 4 * Revenue\_Growth_{Dummy} + \beta 5 * Firm_{Size} + \beta 6 * Firm_{Age} + \gamma Industry + \delta Year + \varepsilon$$

In this equation the *ROA* is the dependent variable. The *Degree_of_Digitalisation* is the independent variable and like Model 1 additional control variables and explanatory variables were included while accounting for industry and year fixed effect. The additional variables included in this model are described below.

Performance measurement and analysis is crucial for steering the organization to realize its strategic and operational goals. ROA offers a different perspective on management's effectiveness by analysing profit earned for every dollar invested in the company assets. Teruel and Solano (2007) argue that ROA should be preferred to measure profitability in the case of SMEs. Also consistent with the study of Shen et.al. (2020), the ROA is used as the key indicator to measure the financial performance.

Similarly, to Model 1, I used the principal component analysis (PCA) to calculate the Degree_Of_Digitalisation. The principle component analysis index (*Degree_of_Digitalisation_Index*) was computed using STATA. To calculate the index, the following variables were used: *Intangible_Assets, Capitalised_Software, R&D, Intangible_Assets_Per_Employee.* The selected variables to compute the Degree of Digitalisation Index are based on Teruel et.al (2022) study which concluded robust results in explaining the degree of digitalisation. All the variables used to compute the Degree_Of_Digitalisation_Index were scaled as % of Total Assets.

None of the variables included in the Degree of Digitalisation PCA Index reported high correlations. All the three variables have a correlation coefficient lower than +/-0.2. Hence, these variables are appropriate to compute an informative principal component. Table 4 provides a summary of these results. Consistently with Model 1, Component 1 (PC1) was used as the final index for Degree_of_Digitalisation_Index with an eigenvalue of 1.2. PC1 includes the positive magnitude of variables Intangible Assets, Intangible Assets per employee and Capitalised Software and the negative magnitude of R&D. Table 4 provides a summary of these results.

The *Degree_of_Digitalisation_Index* was ranked between High, Medium, and Low and three groups were formed with 5,438 observations for two groups and 5,437 observations for one group. Table 4 provides the Descriptive Statistics of Degree of Digitalisation Groups. Thus, a positive value of the PCA index suggests a high degree of digitalisation and a negative value of the PCA index suggests a low degree of digitalisation. As presented in

Table 4, the overall Degree of Digitalisation index mean is -0.001 with the minimum value of -0.800 and the maximum value of 26.360.

In the above equation, the *Degree_of_Digitalisation* is classified as a dummy variable where:

1. The *Degree_of_Digitaisation_High* is the group of firms with high degree of digitalisation with PCA index values between 0.148 and 26.364. The variable takes value of 1 for High degree of digitalisation and 0 for otherwise.
2. The *Degree_of_Digitaisation_Medium* is the group of firms with medium degree of digitalisation with PCA index values between -0.678 and 0.148. The variable takes value of 1 for Medium degree of digitalisation and 0 for otherwise.
3. The *Degree_of_Digitaisation_Low* is the group of firms with low degree of digitalisation with PCA index values between -0.800 and 26.360. The variable takes value of 1 for Low degree of digitalisation and 0 for otherwise.

As explained in the theoretical background and supported by results from prior studies, firms with higher degree of digitalisation tend to have higher profitability. Thus, the $\beta 1$ coefficient is expected to be positive for the groups with high degree of digitalisation and negative for the groups with low degree of digitalisation.

Additional variables should be included in the model to test the second hypothesis. The second hypothesis aims to analyse if firms with higher degree of digitalisation have higher performance during the COVID-19 pandemic. Therefore, the COVID_years variables was included to the model to identify the pandemic years. COVID_years is a dummy variable, which takes value of 1 for pandemic years (2020,2021 and 2022) and 0 for otherwise. Consequently the $\beta 3$ coefficient of the interactive variable *DD_COVID_Interaction* aims to test the second hypothesis. This is an interactive dummy which combines the degree of digitalisation with pandemic years. Thus, $\beta 3$ is expected to be positive for firms with high level of digitalisation during COVID years (Degree_of_Digitalisation_High = 1 and COVID_years =1).

Likewise Model 1, *Revenue_Growth*, *Firm_Age*, *ROA,* and *Firm_Size* are included as control variables. Furthermore, industry fixed effect and year fixed together with robust standard deviations are applied.

The three different regression results are compared to draw conclusions about the second hypothesis and analyse how the degree of digitalisation impacts the firm’s financial performance during the COVID-19 pandemic.

TABLE 4: Degree of Digitalisation Index PCA

Panel A: Correlation of Variables used for Degree of Digitalisation PCA

		(1)	(2)	(3)	(4)
(1)	*Intangible_Assets*	1.0000			
(2)	*Capitalised_Software*	**0.1597***	1.0000		
(3)	*R&D*	0.0093	0.0063	1.0000	
(4)	*Intangible_Assets_Per_Employee*	**0.1379***	0.0125	**-0.0220***	1.0000

Panel B: Principal Components

Component	*Eigenvalue*	*Difference*	*Percent*	*Cum.*
Comp 1	1.217	0.201	0.304	0.304
Comp 2	1.016	0.044	0.254	0.558
Comp 3	0.972	0.178	0.243	0.801
Comp 4	0.794		0.199	1.000

Panel C: Principal Components (Eigenvectors)

Variable	*Comp 1*	*Comp 2*	*Comp 3*	*Comp 4*	*Unexplained*
Intangible_Assets	0.697	0.041	0.025	-0.716	-
Capitalised_Software	0.539	0.361	-0.550	0.526	-
R&D	-0.003	0.805	0.589	0.065	-
Intangible_Assets_Per_Employee	0.473	-0.468	0.592	0.455	-

Panel D: Descriptive Statistics of Degree of Digitalisation Groups

DD Group	*N*	*Mean*	*SD*	*Min*	*Max*
High	5,437	1.100	1.295	0.148	26.364
Medium	5,438	-0.327	0.241	-0.678	0.148
Low	5,438	-0.773	0.033	-0.796	-0.678
TOTAL	16,313	-0.001	1.104	-0.800	26.360

Table 4
Panel A: *provides the correlations of variables used for Degree of Digitalisation PCA Index.*
Panel B*: provides an overview of the Principal Components.*
Panel C: *provides the eigenvectors of the Principal Components.*
Panel D: *provides the descriptive statistics of Degree of Digitalisation Groups*

Note: *The Degree of Digitalisation Index was predicted using PCA component 1 with an eigenvalue of 1.217. The index was then ranked between High, Medium, and Low and three equal groups were formed. Degree of digitalisation refers to the level of digitalisation in a firm. Thus, high degree of digitalisation means that the company is highly investing in digitalisation, which is measured by above variables. The Degree of Digitalisation index is a mix of positive and negative amounts. A PCA index gets a negative value if it is below the mean. Consequently, a negative value of the Degree of Digitalisation Index represents a low level of digitalisation, and a positive value represents that a firm has a high level of digitalisation.*

3.3 Descriptive Statistics

TABLE 5: Descriptive Statistics

Variable	N	p25	p75	Mean	Min	*Max*	*SD*
ROA	16,313	-0.080	0.070	-0.079	-28.650	8.190	0.485
Revenue_Growth_Dummy	16,313	0.000	1.000	0.663	0.000	1.000	0.473
Log_No. Employees	16,313	0.293	2.468	1.547	0.000	7.741	1.415
Leverage	16,313	0.360	0.700	0.571	0.000	35.610	0.563
Liquidity	16,313	-1.420	609.92	1,229.59	-16,535.93	128,536.00	4,826.80
COVID_years	16,313	0.000	1.000	0.512	0.000	1.000	0.500
COVID_Impact_Index	16,313	-0.260	0.080	-0.007	-18.160	30.540	1.049
COVID_Impact_High	16,313	0.000	1.000	0.334	0.000	1.000	0.472
COVID_Impact_Medium	16,313	0.000	1.000	0.338	0.000	1.000	0.473
COVID_Impact_Low	16,313	0.000	1.000	0.328	0.000	1.000	0.470
Intangible_Assets	16,313	0.010	0.350	0.204	0.000	0.950	0.222
Capitalised_Software	16,313	0.000	0.000	0.003	0.000	0.520	0.017
R&D	16,313	0.000	0.000	-0.002	-5.200	0.000	0.049
Intangible_Assets_Per_Employee	16,313	0.000	0.120	0.631	0.000	309.590	5.811
Degree_of_Digitalisation_Index	16,313	-0.760	0.450	-0.001	-0.800	26.360	1.104
Degree_of_Digitalisation_High	16,313	0.000	1.000	0.333	0.000	1.000	0.471
Degree_of_Digitalisation_Medium	16,313	0.000	1.000	0.333	0.000	1.000	0.471
Degree_of_Digitalisation_Low	16,313	0.000	1.000	0.333	0.000	1.000	0.471
Firm_Age	16,313	2.079	3.367	2.760	1.099	4.094	0.843
Firm_Size	16,313	5.376	8.621	7.001	-1.204	13.241	2.304

***Table 5** – reports descriptive statistics for all test variables. Detailed variable description is provided in Appendix F.*

Table 5 presents the descriptive statistics of the main variables used in the empirical analyses which are based on financial data from 2017-2022. The maximum value of Covid impact index (30.540) indicates the PCA index of the firm with highest growth reported in 2020 compared to 2019. The maximum value of the degree of digitalisation index (26.360) indicates the PCA score of the firm with higher degree of digitalisation. A negative ROA value is detected for the firms in the sample. As expected, the firm size, the number of employees, leverage and liquidity have a significant range.

3.4 Correlation Analysis

Table 6 presents the correlation matrix of the main variables used in the regression models and the bolded correlations are significant at the 0.10 level. According to the below correlation matrix, multicollinearity should not be an issue amongst the main variables for both models since the coefficient values are relatively low. A high and significant correlation at 0.10 level of 0.8031 is reported for Log_No. Employees and Firm_Size (measured by logarithm of firm's total assets). The combination of these two variables is not used neither in Model 1 nor in Model 2.

Intangible_Assets is shown to have a positive and significant correlation with Capitalised_Software (0.1596) and firm specific variables (Firm_Size, Log_No. Employees, Firm_Age). A negative correlation is reported for overall Covid Index (-0.0140), but this coefficient is not significant. On contrary, all the correlation coefficients for the COVID_Impact groups are significant at the 0.10 level. Thus, negative, and significant correlations is reported between intangible assets as high and low Covid impact groups with coefficients of -0.0538 and -0.0721 respectively. A positive and significant correlation for the medium impact group with a coefficient of 0.1253 is reported. This highlights the importance to run the regression analysis amongst the three different groups of COVID impact as a relationship might be persistent in group specific observations rather than overall index.

ROA is shown to have a significant negative correlation of -0.3921 with Leverage and significant positive correlations with firm specific variables (Firm_Size, Log_No. Employees, Firm_Age). Furthermore, positive, and significant correlations for Intangible_Assets (0.1031) and R&D (0.1389) is reported. Negative correlations are reported between ROA and medium (-0.0027) and low (-0.0343) degree of digitalisation and positive correlation is reported for the group with high degree of digitalisation (0.0124) and overall degree of digitalisation index (0.0029). Even though, none of these coefficients are significant, it highlights the need to perform the regression analysis between the different levels of the degree of digitalisation as different correlation magnitude is reported for different groups of digitalisation.

TABLE 6: Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	*ROA*	1.0000									
(2)	*Leverage*	**-0.3921***	1.0000								
(3)	*Liquidity*	**0.0857***	**0.0261***	1.0000							
(4)	*Revenue_Growth_Dummy*	**0.1514***	-0.0037	**0.0620***	1.0000						
(5)	*COVID_years*	0.0185	0.0198	0.0191	0.0134	1.0000					
(6)	*Intangible_Assets*	**0.1031***	**0.0515***	**0.0660***	**0.0924***	**-0.0215***	1.0000				
(7)	*Capitalised_Software*	0.0121	0.0189	0.0092	0.0069	-0.0106	**0.1596***	1.0000			
(8)	*R&D*	**0.1389***	0.0077	0.0052	**0.0231***	0.0113	0.0095	0.0062	1.0000		
(9)	*Degree_of_Digitalisation_Index*	0.0029	-0.0055	0.0114	0.0080	-0.0020	0.0187	0.0012	0.0046	1.0000	
(10)	*COVID_Impact_Index*	-0.0003	-0.0107	-0.0162	**0.0254***	0.0063	-0.0140	-0.0029	**-0.0223***	0.0093	1.0000
(11)	*COVID_Impact_High*	**-0.0877***	**-0.0293***	**-0.0885***	**-0.0608***	-0.0024	**-0.0538***	-0.0168	-0.0060	-0.0121	**-0.3406***
(12)	*COVID_Impact_Medium*	**0.1214***	**0.0621***	**0.1148***	**0.0424***	-0.0080	**0.1253***	**0.0238***	**0.0203***	-0.0084	**-0.0735***
(13)	*COVID_Impact_Low*	**-0.0343***	**-0.0331***	**-0.0268***	0.0184	0.0105	**-0.0721***	-0.0072	-0.0144	**0.0206***	**0.4161***
(14)	*Degree_of_Digitalisation_High*	0.0124	-0.0036	0.0127	0.0019	0.0086	0.0086	0.0003	0.0008	**0.7052***	0.0154
(15)	*Degree_of_Digitalisation_Medium*	-0.0027	-0.0130	0.0018	0.0009	-0.0116	0.0032	-0.0113	0.0073	**-0.2088***	-0.0102
(16)	*Degree_of_Digitalisation_Low*	-0.0097	0.0166	-0.0145	-0.0027	0.0030	-0.0118	0.0110	-0.0081	**-0.4963***	-0.0052
(17)	*Firm_Size*	**0.3472***	**0.0410***	**0.4435***	**0.1638***	**0.0492***	**0.2620***	-0.0082	**0.0348***	-0.0063	-0.0172
(18)	*Log_No. Employees*	**0.2443***	**0.1046***	**0.4373***	**0.1317***	-0.0021	**0.2625***	**0.0287***	**0.0291***	-0.0079	**-0.0368***
(19)	*Firm_Age*	**0.2335***	0.0153	**0.1726***	**0.0901***	**-0.0523***	**0.0665***	-0.0141	0.0180	-0.0145	**-0.0407***

		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(11)	*COVID_Impact_High*	1.0000								
(12)	*COVID_Impact_Medium*	**-0.5059***	1.0000							
(13)	*COVID_Impact_Low*	**-0.4945***	**-0.4996***	1.0000						
(14)	*Degree_of_Digitalisation_High*	-0.0091	0.0014	0.0077	1.0000					
(15)	*Degree_of_Digitalisation_Medium*	0.0037	-0.0127	0.0090	**-0.5000***	1.0000				
(16)	*Degree_of_Digitalisation_Low*	0.0054	0.0112	-0.0167	**-0.5000***	**-0.5000***	1.0000			
(17)	*Firm_Size*	**-0.2094***	**0.3156***	**-0.1078***	0.0023	0.0047	-0.0071	1.0000		
(18)	*Log_No. Employees*	**-0.1688***	**0.2746***	**-0.1071***	0.0031	0.0046	-0.0077	**0.8031***	1.0000	
(19)	*Firm_Age*	**-0.0866***	**0.1889***	**-0.1034***	0.0034	-0.0023	-0.0012	**0.3312***	**0.3649***	1.0000

Table 6 *– Provides the correlation matrix of the main variables. * Bolded correlations are significant at the 0.10 level. Detailed variable description is provided in Appendix F.*

4. Empirical Tests and Results

4.1 Regression Model 1

TABLE 7: The Impact of Covid-19 Pandemic on Digitalisation

	Intangible Assets		
	High	**Medium**	**Low**
COVID_Impact_Dummy	0.008**	0.015***	-0.021***
	(2.40)	(4.22)	(-6.33)
Revenue_Growth_Dummy	0.007**	0.007**	0.008**
	(2.31)	(2.36)	(2.52)
ROA	-0.005	-0.005	-0.005
	(-1.55)	(-1.58)	(-1.52)
Firm_Size	0.034***	0.033***	0.033***
	(37.89)	(36.24)	(37.79)
Firm_Age	-0.008***	-0.009***	-0.009***
	(-3.69)	(-3.94)	(-3.98)
Constant	-0.073***	-0.063***	-0.054***
	(-4.09)	(-3.65)	(-3.06)
Industry F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	16,313	16,313	16,313
R-squared	0.396	0.396	0.397

t statistics in parentheses
** p<0.10, **p<0.05, *** p<0.01*

Table 7 *– presents the results of the three different regression analyses: Covid_Impact_High, Covid_Impact_Medium, and Covid_Impact_Low . The regressions test the impact of different Covid-19 levels (High, Medium, and Low) on digitalisation. All the regression analyses account for industry and year fixed effect and robust standard deviations. The detailed description of the variables is presented in Appendix F.*

The regression analysis presented in Table 7 aimed to answer the below formulated hypothesis:

H1: *Firms with higher COVID-19 impact have a higher need to invest in digitalisation.*

According to H1, the $\beta 1$ coefficient is expected to be positive for the groups with high Covid impact and negative for the groups with low Covid impact. Therefore, the results summarised in Table 7 provide empirical evidence to support this hypothesis.

The results suggest that there is a positive and significant relationship at the 0.05 level for firms with high Covid Impact and the dependent variable, intangible assets. This relationship is even stronger and significant at the 0.01 level for the firms with medium Covid impact. The firms with medium covid impact report a higher coefficient than those with high impact (0.015 vs 0.008) and a higher t-value (4.22 vs 2.40). As expected, the firms with low covid impact report a negative and statistically significant relationship at the 0.01 level with a coefficient of -0.021 and a t-value of -6.33. A negative and non-significant relationship is reported between ROA and digitalisation (measured by intangible assets) amongst all the three groups. Firm size is identified to have a positive and significant relationship at 0.01 level amongst all the three groups. Contrary, the firm age is identified to have a negative and significant relationship at 0.01 level amongst all the different Covid levels. The R-squared suggests that approximately 40% of the dependent variable, intangible assets, is explained by Model 1.

These findings support the first hypothesis and provide evidence that firms with higher Covid impact are more likely to invest in digitalisation than the firms with lower Covid impact. This supports the theoretical framework of Verhoef, et.al. (2021) and Gurumurthy, et.al. (2020) which says that digitalisations enables businesses to be creative and think of longer-term growth strategies. The results supports the argument that the digital transformation is about doing new things that were not possible before. The pandemic forced companies highly impacted by this Shock to think differently and find new ways via increasing digitalisation to remain in business and meet customers' needs. The higher positive and significant coefficients for the firms with medium impact also support the argument that Covid Shock was the incentive to boost digitalisation and use it as a hedge during the pandemic. These supports the results of prior papers which concluded that firms are increasingly relying on digital solutions to respond to COVID-19 crisis (Apedo-Amah, et al., 2020; Abidi et al. 2022).

It is concluded that firms highly affected by Covid have a higher need to invest in digitalisation compared to those with lower impact.

4.2 Model 1 – Robust Analysis

TABLE 8: The Impact of Covid-19 Pandemic on Digitalisation (OVERALL INDEX)

	Intangible Assets
COVID_Impact_Index	-0.003**
	(-2.14)
Revenue_Growth_Dummy	0.007**
	(2.34)
ROA	-0.005
	(-1.55)
Firm_Size	0.033***
	(38.03)
Firm_Age	-0.008***
	(-3.80)
Constant	-0.067***
	(-3.83)
Industry F.E.	Yes
Year F.E.	Yes
Observations	16,313
R-squared	0.396

t statistics in parentheses

** p<0.10, **p<0.05, *** p<0.01*

Table 8 *- presents the impact of different Covid-19 impact levels on digitalisation. Only one regression is run with no categorisation between the different Covid levels. The levels of Covid-19 impacts is measured by the magnitude of the overall Covid_Impact_Index. Consequently, a negative value of the Covid Index represents a negative Covid impact, a positive value represents that the impact was very low or firms even experienced growth. The regression analysis accounts for industry and year fixed effect and robust standard deviations. The detailed description of the variables is presented in Appendix F.*

To further test the first hypothesis an additional regression analysis was performed using the Covid Impact Index overall and not categorising the firms between different Covid impact levels. In this regression, the level of the COVID impact is measured by the magnitude of the COVID_Impact_Index. Consequently, a negative value of the Covid Index represents a negative Covid impact, a positive value represents that the impact was very low or firms even experienced growth.

The results summarised in Table 8 support the results of those explained earlier and provide further support for H1. The Covid_Impact_Index has a negative and statistically significant coefficient at 0.05 level. The firms with high Covid impact will have a negative value of the Covid Index. Thus, the negative coefficient multiplied with the negative value of the index suggest a positive relationship on digitalisation. On the other hand, the firm with low Covid impact will have a positive Covid index and thus, a negative impact on digitalisation. This again suggests that firms with higher Covid impact are more likely to invest in digitalisation than the firms with low Covid impact.

4.3 Regression Model 2

TABLE 9: The Impact of Degree of Digitalisation on Financial Performance (ROA) during COVID-19 Pandemic

	ROA		
	High	**Medium**	**Low**
Degree_of_Digitalisation	0.023**	-0.005	-0.008
	(2.18)	(-0.70)	(-0.52)
COVID_years	-0.008	-0.010	-0.016
	(-0.64)	(-0.85)	(-1.35)
DD_Covid_Interaction	-0.023*	-0.016*	0.003
	(-1.70)	(-1.79)	(0.18)
Firm_Size	0.063***	0.064***	0.063***
	(14.24)	(13.96)	(14.28)
Revenue_Growth_Dummy	0.087***	0.086***	0.086***
	(10.20)	(10.18)	(10.22)
Firm_Age	0.050***	0.050***	0.050***
	(10.22)	(10.30)	(10.24)
Constant	-0.619***	-0.617***	-0.609***
	(-15.56)	(-15.58)	(-16.31)
Industry F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	16,313	16,313	16,313
R-squared	0.217	0.217	0.217

t statistics in parentheses

** p<0.10, **p<0.05, *** p<0.01*

***Table 9** – presents the results of the three different regression analyses: Degree_of_Digitalisation_High, Degree_of_Digitalisation _Medium, and Degree_of_Digitalisation _Low . The regressions test the impact of different digitalisation levels (High, Medium, and Low) on firm performance (ROA) during the Covid-19 pandemic. All the regression analyses account for industry and year fixed effect and robust standard deviations. The detailed description of the variables is presented in Appendix F.*

The regression analysis presented in Table 9 aimed to answer the below formulated hypothesis:

H2: *Firms with higher degree of digitalisation are more profitable during the COVID-19 Crisis.*

According to H2, the β3 is expected to be positive for firms with high level of digitalisation during COVID years (Degree_of_Digitalisation_High = 1 and COVID_years =1). Hence, the results summarised in Table 9 do not provide empirical evidence to support this hypothesis.

The results suggest that there is a positive and significant relationship at the 0.05 level for firms with high degree of digitalisation and firm performance, measured by ROA. Only the firms with high degree of digitalisation report a positive and significant relationship on firm performance with a coefficient of 0.023 and a t-value of 2.18. The firms with medium and low degree of digitalisation reports a negative coefficient, but these are not statistically significant. The Covid_years report a negative coefficient amongst all the groups with the lowest coefficient report for the firms with low degree of digitalisation, but none of these is statistically significant. The DD_Covid_Interaction, is the variable of interest to test the H2. A negative and significant relationship at 0.10 level is reported for the groups with high and medium degree of digitalisation. This suggest that regardless of the level of digitalisation, the impact on ROA during Covid years is still negative. A very small and insignificant coefficient is reported for firms with low level of digitalisation. All the other control variables report a positive and significant impact at 0.01 level amongst all the three groups with the highest coefficient being reported for Revenue Growth. The R-squared suggests that approximately 22% of the dependent variable, ROA, is explained by Model 2.

Even though the results are not supporting the second hypothesis, these provide important empirical evidence. The results suggest that purely investing in digitalisation during crisis times it is not sufficient to yield profits. The results do support the theories about digitalisation and the frameworks around implementing a digital transformation. The model of Parviainen et.al. (2017) for example, emphasises that undergoing a digital transofrmation is not an easy nor a cheap process. Businesses must also gain technical experience while utilising their resources and aiming for long term growth strategies. Even though Abidi et. al. (2022) and Teruel et.al. (2022) provide evidence that digitalisation acted as a hedge during the pandemic, they also highlight that the risk of failure in most affected industries is also high. Estrada et.al. (2021), Shen et.al. (2020) and Khan et.al. (2022) draw conclusions that the pandemic had significant impact on the firms' financial performance, leverage, and liquidity. As concluded in the first hypothesis, the firms with higher Covid impact are more likely to invest in digitalisation. However , firms with higher Covid impact are also more likely to have higher financial constraints, which might be an underlying obstacle why higher degree of digitalisation is not resulting in higher performance during Covid years. Betti & Sarens (2020) argue that the implementation of new technologies comes with significant costs, uncertainty, and challenges for an organisation. These challenges could've been further enhanced during the pandemic. Furthermore, Gurumurthy et.al. (2020) also suggests that firms with higher digital maturity tend to have higher performance. But they also argue that a firm at beginning of the digital transformation journey might not see the financial impacts immediately, but at the same time having a low digitalisation maturity and starting the journey of digitalisation might result in cost reduction and hence improved profitability. Consequently, another reason why the higher level of digitalisation is not linked to better performance during Covid times could be the delayed returns on investment.

To conclude, the above results do support the prior studies that firms with higher degree of digitalisation are usually more profitable, but this is not valid during pandemic years. Three main factors are identified which could explain this. First, the inability to undergo a full digital transformation which implies a complete change of business model and a long-term digital strategy. Second, the increased financial constraints because of Covid-19 pandemic and lastly, the delayed return on investments.

4.4 Regression Model 2 – Robust Analysis

TABLE 10: The Impact of Degree of Digitalisation on Financial Performance (ROA) during COVID-19 Pandemic (OVERALL INDEX)

	ROA
Degree_of_Digitalisation_Index	0.009**
	(2.26)
COVID_years	-0.015
	(-1.40)
DD_Covid_Interaction	-0.011**
	(-1.97)
Firm_Size	0.063***
	(14.22)
Revenue_Growth_Dummy	0.086***
	(10.18)
Firm_Age	0.050***
	(10.24)
Constant	-0.612***
	(-15.98)
Industry F.E.	Yes
Year F.E.	Yes
Observations	16,313
R-squared	0.217

t statistics in parentheses

** p<0.10, **p<0.05, *** p<0.01*

Table 10 - *presents the impact of different levels of digitalisation on firm performance during Covid-19 pandemic. Only one regression is run with no categorisation between the different levels of digitalisation. The digitalisation level is measured by the magnitude of the overall Degree_of_Digitalisation_Index. Consequently, a negative value of the Degree of Digitalisation Index represents a low level of digitalisation, a positive value represents a high level of digitalisation. The regression analysis accounts for industry and year fixed effect and robust standard deviations. The detailed description of the variables is presented in Appendix F.*

To further test the second hypothesis an additional regression analysis was performed using the Degree of Digitalisation Index overall and not categorising the firms between different levels of digitalisation. In this regression, the level of digitalisation is measured by the magnitude of the Degree_of_Digitalisation_Index. Consequently, a negative value of the degree of digitalisation index represent a low level of digitalisation, a positive value represents a high level of digitalisation.

The results summarised in Table 10 support the results of those explained earlier and do not provide empirical evidence to support the H2. The Degree_of_Digitalisation_Index has a positive and significant impact on ROA at 0.05 level with a coefficient of 0.009 and a t-value of 2.26. The DD_Covid_Interaction has a negative and significant coefficient at 0.05 level. The firms with high level of digitalisation will have a positive index, and thus, a negative impact on ROA. Whereas the firms with lower degree of digitalisation will have a negative index, and hence, a positive impact on ROA. As explained by Gurumurthy et.al. (2020) this might suggest that firms with very low level of digitalisation might see some costs efficiencies and benefits of increasing digitalisation. However, this also highlights the importance to analyse each group separately and the regression summarised in Table 9 shows a positive coefficient for the interactive variable, but this is not significant for firms with low digitalisation. Thus, no additional conclusions can be drawn.

5. Conclusion and Discussion

The study aims to understand how different levels of Covid impact (High, Medium, and Low) affect the firm's degree of digitalisation and the impact of digitalisation on firm performance during COVID-19 pandemic.

The findings reveal several important insights.

First, COVID-19 has accelerated the adoption of digitalisation in organizations. The pandemic and associated restrictions urged the rapid implementation of digital systems for business continuity. The degree of digitalisation is influenced by the level of COVID-19 impact and it is concluded that firms with higher Covid impact are more likely to invest in digitalisation compared to firms with low Covid impact.

Second, the firms with higher digitalisation to have a better financial performance in non-Covid years. The higher financial performance is not reported during Covid years. The three main factors which could explain this are the inability to undergo a full and complex digital transformation, the increased financial constraints because of Covid-19 pandemic and lastly, a possible lag effect, where the benefits of digitalisation may not be immediately reflected in ROA.

Overall, the study contributes to the existing literature by providing empirical evidence on the relationship of different levels of Covid impact and digitalisation. Additionally, providing evidence about the relationship between digitalisation and firm performance during the COVID-19 crisis. The findings emphasize the nuanced relationship between the degree of digitalisation and financial performance during the COVID-19 crisis. It emphasizes the importance of considering the specific context and stages of digital transformation when analysing the impact of digitalisation and firm outcomes during COVID-19 pandemic. The findings have implications for policymakers advocating for digital transformation initiatives and provide valuable insights for organizations navigating the challenges of the digital era.

Limitations and Future Research:

The study highlights the need for further research on the impact of the COVID-19 crisis on digitalisation and firm performance. The specific effects of COVID-19 on the level of digitalisation and the use of new technologies, as well as the persistence of the digital gap and its effects on performance, require deeper investigation.

This study was not able to draw sound and significant conclusions of what might be the underlying factor of not seeing higher firm performance for firms with high level of digitalisation during the pandemic. This might be due to limited KPIs to measure the degree of digitalisation and restrictive time frame which does not account for post-Covid impact. Future research is needed to understand what new and emerging key performance indicators are arising to measure digitalisation and how these reflect the firm's performance. Gurumurthy et.al. (2020) provide a solid strating point to identify the new digital KPIs by decribing best practices of the seven digital pivots (See Appendix D).

Furthermore, at the time this study was conducted, there was no sufficient data to analyse the post pandemic recovery and the impact on digitalisation. OECD (2020) suggest that digital maturity provides business resillience and increase the changes of faster recovery. These results are supported by Abidi et.al. (2022) and Teruel et al (2022) making it an interesting and important field for further research. Policy advisors might benefit from understanding the current gap between higher and lower digital maturity firms. It is not yet statistically tested whether firms who heavily invested in digitalisation during crisis times started to see financial benefits post-crisis. Estrada et.al. (2021) suggests that companies will require at least one year to recover from the pandemic and Busato et.al. (2021) concluded that pre-Covid conditions are reached only after two years.

And lastly, in the most affected sectors by COVID-19 pandemic, where firms had to adjust to "contactless" way of doing business, the digital transformation happened in a rush and with no preparedness.(OECD Studies on SMEs and Entrepreneurship, 2021) Thus, creating an opportunity of increase in cyber-attacks. Furture research is needed to understand what are the long lasting effects of rushed digitalisation and the risks of cyber security on the long term firm performance. This highlights that the digital transformation might be a game changer for organisation, but it also increases the risk of failure unles it is done in the correct way. (Abidi, El-Herradi, & Sakha, 2022) (Betti & Sarens, 2021) (Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020)

"This is because digitalisation only works when people count. In more ways than one". Prof. Dr. Carsten Busch, President of the University of Applied Sciences, Berlin (Schmiedchen, Kratzer, Link, & Stapf-Finé, 2022)

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7. Appendix

7.1 Appendix A. Flow Model for Discussion on Digital Transformation

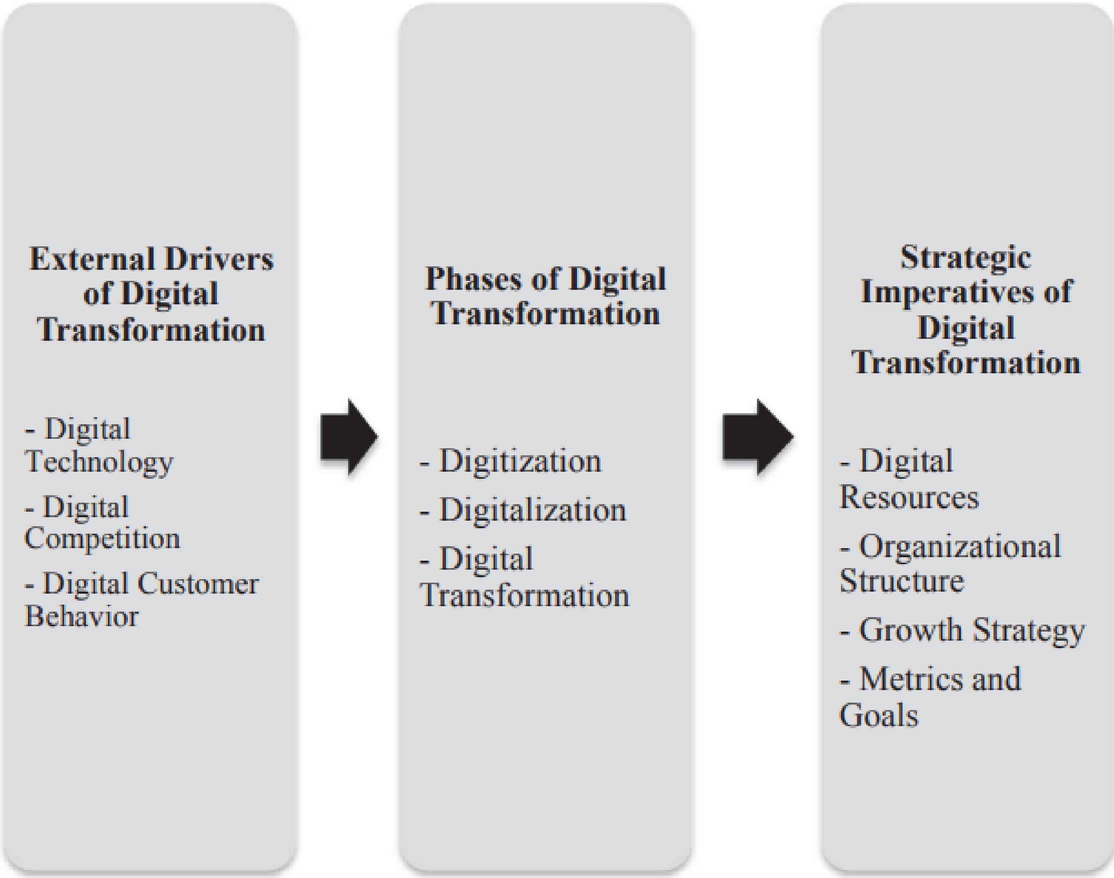

Figure 1 *– Flow Model for Discussion on Digital Transformation (Verhoef, et al., 2021)*

7.2 Appendix B. Understanding digital analytics: An organizing framework.

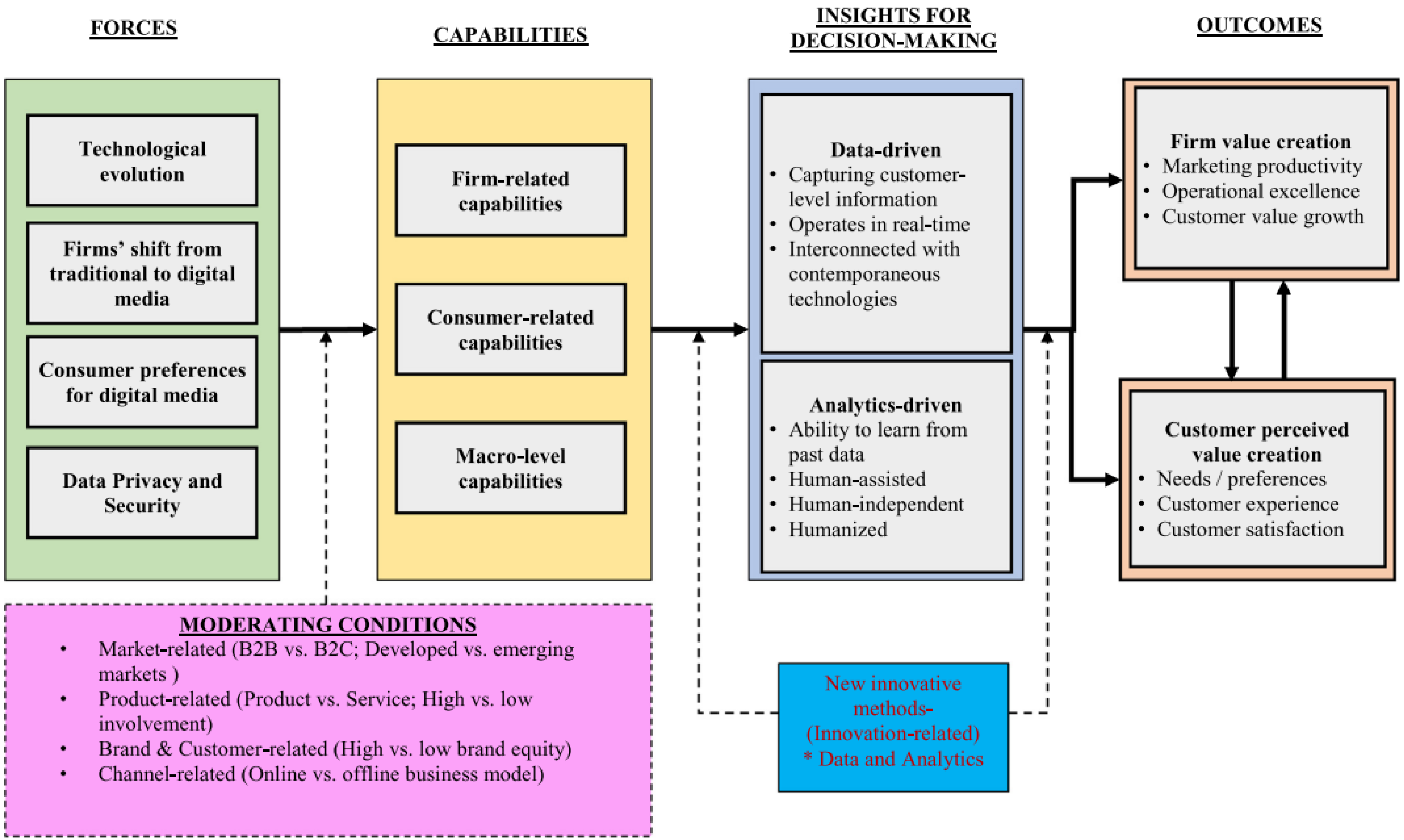

Figure 2 *- An organising framework to understand digital analytics. (Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020)*

7.3 Appendix C. The Seven Digital Pivots

Digital pivot	Description
Flexible, secure infrastructure	Implementing technology infrastructure that balances security and privacy needs with the ability to flex capacity according to business demand.
Data mastery	Aggregating, activating, and monetizing siloed, underutilized data by embedding it into products, services, and operations to increase efficiency, revenue growth, and customer engagement.
Digitally savvy, open talent networks	Retooling training programs to focus on digital competencies, and staffing teams through flexible, contingent talent models to rapidly access in-demand skill sets and flex the organization's workforce based on business need.
Ecosystem engagement	Working with external business partners including R&D organizations, technology incubators, and startup companies to gain access to resources such as technology, intellectual property, or people to increase the organization's ability to improve, innovate, and grow.
Intelligent workflows	Implementing and continuously recalibrating processes that make the most of both human and technological capabilities to consistently produce positive outcomes and free up resources for higher-value actions.
Unified customer experience	Delivering a seamless customer experience built around a 360-degree view of the customer that is shared companywide so that customers experience coordinated digital and human interactions that are useful, enjoyable, and efficient in immersive, engaging environments.
Business model adaptability	Expanding the organization's array of business models and revenue streams by optimizing each offering to adapt to changing market conditions and augment revenue and profitability.

Figure 3 *– The Seven Digital Pivots (Gurumurthy, Schatsky, & Camhi, 2020)*

7.4 Appendix D. Best Practices of the Seven Digital Pivots

Digital pivot	Top three best practices in order of importance
Flexible, secure infrastructure	1 Automate cloud cost management and optimization 2 Leverage platform-as-a-service (PaaS) or managed service provider (MSP) models 3 Automate provisioning and operations of cloud infrastructure
Data mastery	1 Embed data-driven insights into tools employees use every day 2 Democratize access to data/insights through self-service portals 3 Offer products/services to clients powered by data we collect
Digitally savvy, open talent networks	1 Hire freelancers/independent workers to extend the core employee workforce 2 Hire gig workers who are paid by the task (or microtask) 3 Engage crowd workers who compete to participate in projects
Ecosystem engagement	1 Sell solutions together in the market 2 Cocreate intellectual property and/or solutions 3 Ensure interoperability with some competitors' digital solutions
Intelligent workflows	1 Establish an automation "center of excellence" 2 Automate business decision-making (e.g., resource allocation, dynamic pricing) 3 Automate routine customer and/or employee interactions with chatbots/conversational AI
Unified customer experience	1 Provide multi/omnichannel touchpoints 2 Capture and incorporate the voice of the customer into decision-making 3 Maintain a single 360-degree view of the customer
Business model adaptability	1 Offer digital services 2 Operate a digital marketplace 3 Offer digitally connected products

Figure 4 - *Best Practices of the Seven Digital Pivots (Gurumurthy, Schatsky, & Camhi, 2020)*

7.5 Appendix E. Model for Tackling Digital Transformation.

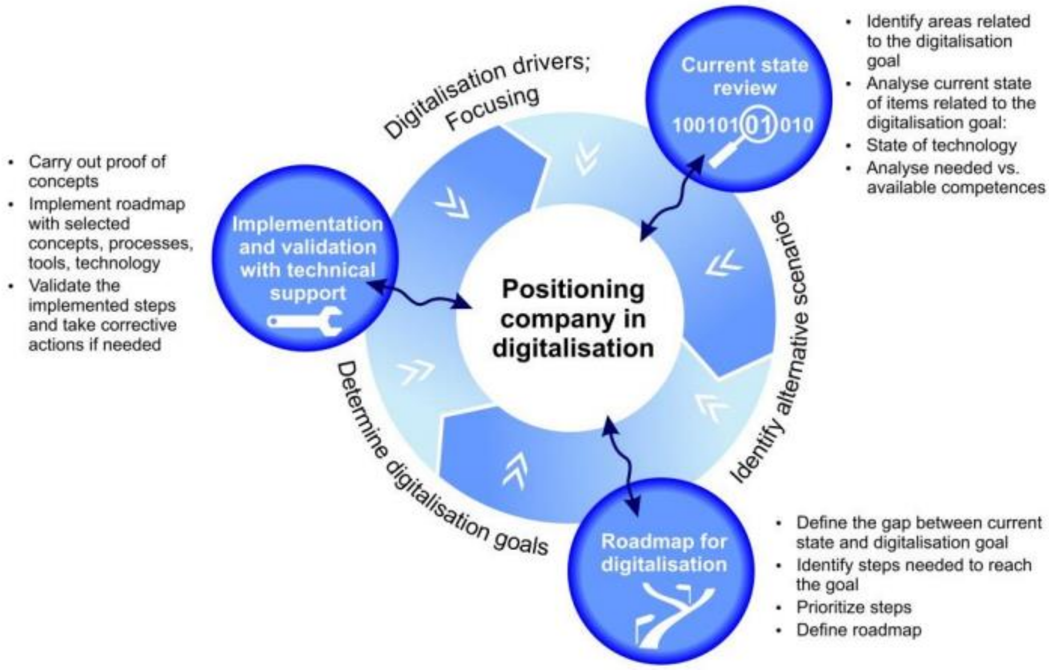

Figure 5 *- Model for Tackling Digital Transformation (Parviainen, Kääriäinen, Tihinen, & Teppola, 2017)*

7.6 Appendix F. Variable Definitions

TABLE 11: Description of Variables

Variable	Description
FIRM PERFORMANCE	
ROA	Income before extraordinary items available for common divided by fiscal yearend total assets
Revenue_Growth_Dummy	Dummy variable which takes value 1 if the firm experienced positive revenue growth from year on year and otherwise, takes value of 0.
COVID VARIABLES	
No. Employees	The logarithm of the number of staff employed by a firm at a specific point in time plus 1. *Log (No.Employees+1)*
Leverage	The ratio of Total Liabilities over Total Assets.
Liquidity	FCF (Free Cash Flow). FCF is calculated using the following formula: EBITDA + depreciation and amortization – change in working capital – capital expenditure
COVID_years	Dummy variable which takes value 1 for Covid Year (2020, 2021, 2022) and 0 for non-Covid years (2017, 2018, 2019)
COVID_Impact_Index	A principle component analysis index was computed using STATA. To calculate the index, the change % between 2020 vs 2019 years for the following variables were used: No._Employees, Liquidity, Leverage (Change % of X=(X_2020-X_2019)/X_2019). The Component 1 (PC1) was used as the overall index.
COVID_Impact_Dummy	The COVID_Impact_Index was ranked between High, Moderate and Low impact and three equal groups were formed with 946 firm specific observations per group. COVID_Impact refers to the negative impact. In the regression analysis, it is classified as a dummy variable where: 1. *COVID_Impact_High* is the group of firms with High Covid Impact with PCA Index values between -18.163 and -0.207. The variables takes value of 1 for High Impact and 0 for otherwise. 2. *COVID_Impact_Medium* is the group of firms with Medium Covid Impact with PCA Index values between -0.206 and -0.005. The variables takes value of 1 for Medium Impact and 0 for otherwise. 3. *COVID_Impact_Low* describe the firms with Low Covid Impact with PCA Index values between -0.004 and 30.545. The variables takes value of 1 for Low Impact and 0 for otherwise.

DEGREE OF DIGITALISATION	
Intangible_Assets	The ratio of Intangible Assets as % of Total Assets.
Capitalised_Software	The ratio of Capitalised Software as % of Total Assets.
R&D	The ratio of R&D as % of Total Assets.
Intangible_Assets_Per_Employee	Total Intangible_Assets divided by the No._Employees during a specific period. This was then scaled as % of Total Assets.
Degree_of_Digitalisation_Index	A principle component analysis index was computed using STATA. To calculate the index, the following variables were used: Intangible_Assets, Capitalized_Software, Intangible_Assets_Per_Employee. The Component 1 (PC1) was used as the overall index.
Degree_of_Digitalisation_Dummy	The Degree_of_Digitaisation_Index was ranked between High, Moderate and Low impact and three equal groups were formed. In the regression analysis, it is classified as a dummy variable where: 1. *The Degree_of_Digitaisation_High* is the group of firms with high degree of digitalisation with PCA index values between 0.148 and 26.364. The variable takes value of 1 for High degree of digitalisation and 0 for otherwise. 2. *The Degree_of_Digitaisation_Medium* is the group of firms with medium degree of digitalisation with PCA index values between -0.678 and 0.148. The variable takes value of 1 for Medium degree of digitalisation and 0 for otherwise. 3. *The Degree_of_Digitaisation_Low* is the group of firms with low degree of digitalisation with PCA index values between -0.800 and 26.360. The variable takes value of 1 for Low degree of digitalisation and 0 for otherwise.
FIRM SPECIFIC CONTROL VARIABLES	
Firm_Age	The logarithm of the time since Company Initial Public Offering Date to 31/12/2022.
Year	The Calendar Year
Industry	Standard Industry Classification Code (SIC) retrieved from Compustat CRSP Database.
Firm_Size	The logarithm of total assets
INTERACTIVE VARIABLES	
DD_Covid_Interaction	A dummy variable for each model as listed below: DD_Covid Years_High = DD_Dummy_HM * Covid_years DD_Covid Years_Medium= DD_Dummy_Low* Covid_years DD_Covid Years_Low = DD_Dummy_Decreased * Covid_years
DD_Covid_Index	Degree_of_Digitalisation_Index * Covid_years

Table 11 *– provides a detailed description of the variables used to run the regression analyses for Model 1 and Model 2.*