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Resource Re-orchestration and firm survival in crisis periods: The role of business models of technology MNEs during COVID-19

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ABSTRACT

Using data from world-leading digital-driven/technology multinational enterprises (DTMNEs), we draw from the resource orchestration theory to investigate the associations between business model (BM) drivers and firm performance during crisis periods. Drawing on data from the COVID-19 pandemic period, we deploy diverse analytical approaches including multivariate linear regressions and aggregated composite index statistical methods in examining how the BMs of our sampled DTMNEs drive firm performance. Our study highlights six methodological approaches that can be utilised by decision-makers in examining which variables in their BM drive better firm performance. Our findings revealed that the principal component analysis and multicriteria decision analysis (PROMETHEE methods) that espouse the use of aggregate composite index can provide significant and consistent predictive results in comparison to the traditional linear methods when examining the association between BM and firm performance during crisis periods. The paper provides policy and managerial implications on how firms and decision-makers can bolster business continuity, resilience, and plasticity by using analytical lenses that identify optimum resource orchestration during crises.

1. Introduction

For companies to remain competitive and sustainable, unique resource orchestration that provides the economic foundations for success is required (Teece, 2007; Kohtamäki et al., 2020; Sjödin et al., 2022). However, irrespective of size and industry, there are two variables' firms can manipulate to make profits: either selling more (revenue) or reducing costs of operations (expenditure). These two factors underpin corporate decisions about resource acquisition, configuration, and the business model (BM) used to achieve long-term value. Besides profits, a BM has two principal functions: creating value for customers and capturing value for firms (Chesbrough, 2010; Sjödin et al., 2020). Companies competing to gain an advantage through BM (Casadesus-Masanell and Ricart, 2011) must create and deliver value to customers, and "*convert payment received into profits*" (Teece, 2010: 173; Malmström et al., 2015).

Therefore, corporate executives must understand what their BM is, its underlying components and assumptions, as well as the pathways needed to achieve them (i.e., their value proposition, the underlying infrastructure and customer base (Heikkilä et al., 2017). BMs are comprised of a combination of components, and it is, therefore, critical to analyse the relationship between these components and how they lead to firm performance (Latifi et al., 2021; Heikkilä et al., 2017; Zott et al., 2011). As such, the relationship between profit and resource acquisition provides potential antecedents and consequences of the BM design (Amit and Zott, 2015; Clauss, 2023). However, the purpose of a BM is more than assuring profit maximisation. Rather, the relationship between the components of the model and the continuous orchestrations of relevant available resources remains a critical part of business continuity (Chroneer et al., 2015; Kohtamäki et al., 2020; Sjödin et al., 2022).

Interestingly, all BM aimed at value creation and value capture in the

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21st century seem to be driven by digital technologies such as blockchain, the internet of things (IoT), machine learning and artificial intelligence (Chirumalla, 2021; Sjödin et al., 2021). The evolution of the internet has catalysed implications for BM development (Budler et al., 2021; Ancillai et al., 2023). Such technology enables the connection of information, ideas, and knowledge while allowing flows of data, goods, services, investment, and capital between nations, industries, companies and individuals. Such new connectivity-enabling technology increases competition among companies while also providing opportunities for business model innovation (BMI) (Jovanovic et al., 2021; Kraus et al., 2020a; Leminen et al., 2020). Digital transformation has resulted in significant and innovative changes to BMI in order for firms to remain competitive (Teece, 2010; Zott et al., 2011; Burström et al., 2021).

Given that digital transformation is altering the approach of businesses in creating and capturing value, there is a trend towards increasingly novel design in the orchestration of the components of a company's BM (Foss and Saebi, 2017; Zott and Amit, 2007; Linde et al., 2021). The purpose of developing new BMs), is to create and deliver value to customers and/or capture new value (Yunus et al., 2010). To activate the overlooked value sources within firms or create new systems which are difficult to imitate, a change in at least one of the three, i.e. value creation, delivery or capture needs to be accomplished (Amit and Zott, 2012; Johansson and Malmstrom, 2013; Malmström and Johansson, 2017). However, due to changes in industry dynamics, market structures, and increasing complex demands from value-conscious consumers, competition from global players has intensified (Ancillai et al., 2023; Ibarra et al., 2018).

The BMI and strategic management literature is yet to show how the internet revolution and increased globalisation has enabled some firms to redefine their BM by re-thinking what they do, how, when and where they do it (Jovanovic et al., 2021; Kraus et al., 2020a; Filser et al., 2021; Leminen et al., 2020). Consequently, agility and ambidexterity have become the principal resources (e.g., tangible and intangible) by which high-interest stakeholders measure long-term corporate success. Agility delineates a company's ability to learn, respond, adjust and adapt to changes in a dynamic environment with high velocity and to be flexible (Sjödin et al., 2020). Firms achieve this by applying established knowledge while also learning from new experiences. As such, agility implies learning, flexibility, velocity, and response to change (Campanelli and Parreiras, 2015).

Therefore, in this study, agility is defined as the *ability of a company to operate profitably in a rapidly changing and continuously fragmenting global market environment by producing high-quality, high-performance and customer-focused goods and services* (Tsourveloudis and Valavanis, 2002; Djaja and Arief, 2015; Clauss et al., 2019; Bhatti et al., 2021). Clauss et al. (2021) argued that ambidextrous firms are agile and swift and can respond to changes in competition through resource orchestration. The term technology or digitally-driven multinational enterprise (DTMNEs) used in this study represents the world's most profitable AI analytics and digital technology firms (Ritter and Pedersen, 2020). Hence, digital BM drivers in this study include the factors that sustain agility and influence the performance and value of the MNEs used in this study.

Whilst the business strategy and accounting and finance literature, such as Kaplan and Norton (1992) and MacDonald and Ryall (2004), used performance measurement concepts to explain the factors behind corporate agility, the BMI literature has been inadequate in showing how companies can continuously engage in digital innovations to sustain performance and remain agile during crisis periods (Breier et al., 2021; Huikkola et al., 2022; Mariani et al., 2023; Vatankhah et al., 2023). Hence, we follow the work of Leone et al. (2022); Chirumalla (2021); Nasiri et al. (2020); Chatterjee et al. (2022); and Peruchi et al. (2022) to gain insight into how technology firms remained agile during the COVID-19 pandemic.

Within the post-COVID-19 business environment, incumbent businesses face two significant challenges. Firstly, how do successful firms create a financially sustainable BM, responding to requirements of remaining a "going concern" while having the necessary flexibility and agility to respond to unpredictable crises? We know from previous studies that change in the environment is a determinant of BMI, specifically in situations like the COVID-pandemic (Clauss et al., 2019; Clauss et al., 2022; Kraus et al., 2020b). The second challenge for businesses in the post-COVID-19 business environment, is how do incumbent firms re-deploy existing key resources to reconstruct, capture and deliver value during times of crises and uncertainties (Kimani et al., 2020; Jovanovic et al., 2021)? The key challenge lies in how firms re-capture value using their existing BM during complex unpredictable smokescreen situations (Simon, 2017).

Thus, despite the significant body of research that focuses on BMI (Simmons et al., 2013; Ancillai et al., 2023), the development of dynamic capabilities (Teece, 2018), and the recreation of value in complex and competitive eco-systems (Burström et al., 2021), there has been limited research on how management teams can immediately adapt BMs by re-orchestrating resources to respond to unplanned changes in corporate needs as they arise. Whilst BM has always been intimately associated with digitalisation and new forms of connectivity-enabled innovations (Burström et al., 2021), how technology multinational enterprises in the most advanced economies re-adapt their BM to respond to change has not been studied. Specifically, how and why the world's leading ambidextrous technology MNEs have sustained value utilising composite indicators of different business drivers to withstand failure during the COVID-19 pandemic is an exciting discourse for the BM community (Kraus et al., 2020b; Clauss et al., 2022; Wendt et al., 2022).

In a complete departure from the extant literature, this study argues firstly that crisis periods render well-intended BMs irresponsive to changes in varied directions, and the COVID-19 pandemic has proved so (Choi, 2021; Kraus et al., 2020b). Secondly, using individual factors that drive DTMNEs, BMs usually fail to predict changes and do not capture the planned efforts of firms dealing with constant change during crisis periods. Hence, this study utilises crucial analytical approaches, including traditional pooled OLS regression, to understand the BM drivers of the 56 most profitable DTMNEs in our dataset. We also used accounting ratio predictors in measuring growth rates when resources were re-orchestrated during the crisis. To establish and investigate the linkages between the dummy variable on firm performance, we embraced the effort-strain or the elasticity model in analysing how a unit change in each driver affected sales revenue. Composite analysis consisting of Principal Component Analysis (PCA) and Multi-Criterion Decision Analysis (MCDA) was deployed to understand the aggregated quality of DTMNEs' BM drivers.

Our study contributes to the resource orchestration theory by arguing that to achieve optimal corporate financial performance during crisis periods, a multi-dimensional resource reconfiguration across the scope and depth, and at different levels of firms, should be adopted.

2. Theory and hypothesis

2.1. Resource orchestration theory

As an extension of the resource-based view (Barney, 1991; Penrose, 1959), resource orchestration theory argues that firm performance is explained by how firms manage or orchestrate their resources (Carnes et al., 2017; Sirmon et al., 2011). The resource-based view advocates that possessing valuable and heterogeneous resources leads to competitive advantage and superior firm performance (Chadwick et al., 2015; Sirmon et al., 2011). The heterogeneity of a resource manifests in its value, rareness, inimitability, and non-substitutability (Barney, 1991). However, an increasing number of empirical studies, such as Carnes et al. (2017) and Kraaijenbrink et al. (2010), have criticised the resource heterogeneity theory for being a necessary but insufficient condition for generating competitive advantage. Instead, resources must be actively deployed, recombined and managed to generate synergistic effects (Gruber et al., 2010; Sirmon et al., 2011) and optimise value creation

(Sirmon et al., 2007; Peteraf and Barney, 2003).

To address the limitation of the resource-based view, resource orchestration theory argues that resource management actions designed to orchestrate firm resources and capabilities make a difference (Sirmon et al., 2007). This logic suggests that firms need to be able to orchestrate resources to realise joint effects from interconnection among resources rather than the independent effects of individual resources to sustain performance and competitive advantage (Chirico et al., 2011; Zaefarian et al., 2013). Specifically, they need to carefully structure, bundle and leverage resources to generate a portfolio that creates value for customers and competitive advantages for firms (Carnes et al., 2017). Structuring action relates to acquiring external resources and divesting unpromising resources. Bundling action includes stabilising to incrementally improve existing capabilities, enriching current capabilities, and pioneering to create new capabilities (Sirmon et al., 2011). Finally, leveraging action involves mobilising to form requisite capability configurations and deploying to exploit capabilities (Sirmon et al., 2011; Wendt et al., 2022).

The resource orchestration theory suits the BM approach (Bigelow and Barney, 2021) because it highlights the necessity of the co-alignment of multiple factors (Chirico et al., 2011) and the requirements that drive a firm's BM (Sirmon and Hitt, 2009; Foss and Saebi, 2017). To understand the impacts of BM change during crisis, how various business components are simultaneously bundled and reconfigured is crucial. Resource orchestration theory has been used in a wide range of areas. Cui et al. (2017) explored how resources are orchestrated under different strategies to achieve e-commerce-enabled social innovation in villages. Yu et al. (2021) applied resource orchestration theory to explore how healthcare organisations managed and bundled their data-driven culture and digital technology orientation to develop big data analytical capability that generates superior operational performance. Queiroz et al. (2022) observed how resource orchestration can build supply chain resilience.

The resource orchestration theory is, therefore, an appropriate theoretical lens for exploring the relationship between BM change and firm performance during crisis periods. During the 2020 pandemic crisis, several MNEs adapted their BM to meet the needs of the time. While the ways in which the factors that drive BM can be reconfigured to enhance firm financial performance and firm value are largely unknown, this maintains significant managerial importance.

2.2. Pandemic crisis, firm performance and firm value

According to resource orchestration theory, firms need to acquire, accumulate, and divest relevant strategic resources to structure a new resource portfolio to create a fit with the external environment (Sirmon et al., 2011). Financial slack resources play a pivotal role in resource orchestration. As a key type of financial slack, cash flow lays the foundation for firms to absorb an economic shock and restructure new resource portfolios to build resilience (Tognazzo et al., 2016). Following this logic, we first argue that firms with more financial slack are more likely to have better performance and value, especially during crisis.

Financial slack enhances the managerial tolerance of risk (Clarke and Liesch, 2017) and more likely stimulates the likelihood of structuring a new resource portfolio and BM (Cyert & March 1963). Singh (1986) found that abundant financial resource drives high levels of innovation because it brings psychological safety. It also acts as a cushion that allows firms to adapt successfully to external pressures, to initiate strategic changes to the external environment (Bourgeois, 1981), and to help protect firms against environmental changes (Cyert & March 1963; Sirmon et al., 2007). Specifically, available cash can easily be re-deployed to purchase new types of machinery, hire talented people, or invest in R&D and marketing build new capabilities and facilitating the transfer to a more profitable BM during a crisis (Mishina et al., 2004; Mousa and Reed, 2013). Meanwhile, firms will all have different strategic alternatives available to innovatively restructure resource portfolios and their BM when responding to a crisis. For example, Tan and Peng's (2003) research supported the argument that high liquidity was associated with better performance among Chinese firms during economic transition. The research by Gittell et al. (2006) highlighted that US airline companies with the greatest financial reserves and low levels of debt exceeded their previous performance. By using longitudinal data to track Italian firms before and after the 2008 world financial crisis, Tognazzo et al. (2016) confirmed that financial slack is positively related to firm performance during the crisis. Hence, we present our first hypothesis as follows.

Hypothesis 1. If cash flow increases during a crises period, then firm performance will improve and additional value will be created

We argue that firms investing significantly in R&D are more likely to have better firm performance and value, especially during a crisis period. Existing research suggests that increasing investment in R&D has a positive association with firm performance during crisis periods. Thus, investing in R&D brings competitive benefits via existing product cost reductions, product quality improvements and new product innovations (Henderson and Cockburn 1994). More importantly, investment in R&D can be viewed as an option to expand in the development of new products in the future (Ferreras-Méndez et al., 2021). It can also be seen as a special type of slack resource because it provides firms with the ability and flexibility, rather than the obligation, to undertake future actions (McGrath, 1997). Given that R&D investment provides firms with a variety of future opportunities to orchestrate their resource portfolio and BM flexibly and rapidly during a crisis (Lee et al., 2008; McGrath and Nerker 2004), it should be considered a crucial driver of superior performance during crisis periods.

Hypothesis 2. If R&D expenditure increases during crisis periods, then firms will create value to sustain and improve financial performance

2.3. Business model, firm performance and firm value for AI and digital technology-driven businesses

According to the resource orchestration theory, how resources are orchestrated can differentiate firm performance during a crisis. A BM represents the overall manifestation of how firms' structure, bundle, and leverage resources to create value (Bigelow and Barney, 2021). A BM sets out the "content, structure, and governance of transactions designed to create value through the exploitation of business opportunities" (Zott and Amit, 2007). A BM is also a unique configuration of critical resources and three mutually enforcing elements; value proposition, value creation, and value capture (Foss and Saebi, 2017). This is also the case for digital BMs.

AI analytics and digital technology-driven businesses are evolving, and consequently, it is imperative for managers to adopt a more growth-oriented BM that is flexible and innovative to facilitate value creation in fast-changing and volatile environments to guarantee business continuity and growth (Breier et al., 2021; Cheah et al., 2018; Giesen et al., 2010). Mason and Mouzas (2012) argued that companies need to be ready to adapt rapidly and easily respond to fast-changing market demands during crises. A digital-driven BM that is flexible supports timely and intensive resource portfolio reconfiguration to exploit emerging opportunities during a crisis (Casadesus-Masanell and Ricart, 2011). A digital BMI that emphasises growth rate provides managers and decision-makers with the required flexibility in restructuring organisational resources in the most productive manner during crisis periods (Farrell and Oczkowski, 2002). Since crisis periods are characterised by high uncertainties and market volatility, a BM that puts growth at the centre provides better growth opportunities for firms (Pohle and Chapman, 2006). BMs that prioritise growth rates are usually flexible, future-oriented and promote innovativeness (Amit and Zott, 2010; Trahms et al., 2013). Although increasing sales represents a better measure of growth, decision-makers should stress test their sales forecast when considering BM effectiveness during crisis periods.

Hypothesis 3. If effort strain on sales (i.e., elasticity) is increased during crisis period, then firms will create value to sustain and improve financial performance.

BMs have a decisive role in envisioning how organisations create, deliver, and capture firm value. In devising BMs, managers make strategic choices and allocate resources using different drivers, such as R&D, marketing, intangible assets, capital expenditures, and ESG, among others, that could impact business performance (Chan et al., 2017; Chaudhuri et al., 2016). Although there are some differences in the components of BMs (Shafer et al., 2005; Heikkilä et al., 2017), there is no doubt that a consistent BM enhances firm performance. The interactions of the different BM drivers help to generate new revenues, avoid loss of sales, and provides continuity in leveraging opportunities. On the other hand, failure to understand and implement BM may result in severe consequences, such as remaining as a going concern, insolvency, and bankruptcy.

Firms' BMs were under heavy stress during the global COVID-19 pandemic (Priyono et al., 2020; Clauss et al., 2021; Kraus et al., 2020b; Wendt et al., 2022). Decision-makers needed to act promptly; forced to adjust their BM rapidly by redirecting resources (financial and non-financial) across different business areas (e.g., managing R&D and marketing expenses, investing in patents and intangible assets, enhancing capital expenditures and investments in connectivity-enabling technologies. However, when they are misunderstood and poorly implemented, uncertainty levels for the going concern increase and this leads to unexpected losses, Whilst Shafer et al. (2005) argued that a consistent BM enhances firm performance, the components of the BM will differ from one MNE to another. Given that the interaction among BM drivers helps generate new revenues, firms are able to avoid losing sales by leveraging opportunities. Consequently, decision-makers must act promptly by re-orchestrating existing resources to improve business performance, survivability, and solvency.

As noted by the resource orchestration theory, an analytical thinking approach is needed for understanding resource configuration and BMI (Sirmon et al., 2011; Bolzani and Luppi, 2021). Specifically, this is to help understand the system's parts as BM drivers and to identify relevant properties and behaviours taken separately when dealing with ambiguity. As argued by Chan et al. (2017) and Chaudhuri et al. (2016), determining the individual significance of well-known BM drivers, such as R&D, marketing expenses, intangible assets, capital expenditures, and ESG in relation to firm performance and value is unexplored. To diminish the complexity and reduce ambiguity around resource configuration during the 2020 pandemic crisis, our research utilised a systematic thinking approach that allowed for an aggregated index of the BM drivers using Multicriteria Decision Analysis (MCDA). According to Karam et al. (2020) and Petkov et al. (2007), MCDA methods (utilitarian or outranking) help to establish a holistic view of a system, analyse its behaviour, and support decisions by aggregating multiple attributes.

Although there are some MCDA approaches reported in the literature to support ranking strategies (Husain et al., 2021) or selecting options (Basile et al., 2021) in BM, this information has not been embedded in an analytical thinking approach using multivariate statistical analysis to determine its contribution to firm performance. In other words, this research aims to create a global MCDA indicator to investigate the level of flexibility (aggregated quality) in terms of financial commitments and BM support. To the best of our knowledge, our approach has not been considered in the literature on BM during crisis periods.

In empirical finance, a similar MCDA approach was considered by Guney et al. (2020), who sought a global indicator (aggregated quality) for corporate governance and its linkage to firm performance. However, this study uses the MCDA composite index to investigate the linkages between multiple BM drivers on firm performance and value creation during the Covid-19 pandemic period. To test hypothesis 3, we postulate that the MCDA composite index, aggregated quality of BM drivers, is positively associated with firm performance and value during the 2020 pandemic crisis.

Hypothesis 4. If MCDA composite index is utilised during crisis period, then firms will create value to sustain and improve financial performance.

3. Methodology

3.1. Sample procedure

Our initial sample data comprised 540 top-tier technology MNEs from seven countries including China, UK, Germany, India, Japan, Sweden and the USA. The data collection process was particularly enlightening in observation of some interesting consistencies in the way the top DTMNEs around the world reorchestrated existing resources to meet (changing market needs?) during the COVID-19 crisis. Thus, the Bloomberg equity screening functionality as well as the "industry search criteria" was utilised in selecting and focusing on the top DTMNEs. Since our study focused on IT and AI-driven MNEs, we included in our sample only those firms whose operations were driven either by AI analytics and/or digital technologies. Our filtering results for AI analytic and digital-driven technology firms returned 156 highly-ranked IT and AI-driven MNEs in our second sample. In arriving at the final sample size, we noted that some MNEs in our samples were still not fulfilling the definition of AI-driven tech MNEs.

We confirmed this by manually checking the operations of the final sample firms from their websites and annual statements. Consequently, we eliminated a further 76 MNEs from our sample size. Also, since our study only focused on the COVID-19 crisis periods between January 2020 and December 2020 we excluded 24 further firms from the remaining 80 firms where there was inconsistent data or missing data for all the periods between January 2020 and December 2020. Following the data cleaning, we arrived at a final sample of MNEs comprising 56 highly ranked global DTMNEs.

To ensure the robustness of the data and findings, we undertook further manual checks from the annual reports and websites of the 56 sampled MNEs in our dataset to ensure that they adapted their BM either in the form of AI analytics, technologies for automation or digitalisation in their operations. To be clear, the term digital-driven BM used in this study refers to BM for IT and AI-driven companies. Our firm-specific characteristics and country-of-origin of the sampled MNEs are presented in appendix 1.

We operationalised the data collection in four stages. First, following the research hypothesis, we used the Bloomberg equity screening functionality to collect data on DTMNEs from the Bloomberg database. Second, we used the industry search criteria within Bloomberg to identify the top-ranking global DTMNEs. Bloomberg's database provides all the listed MNEs. Hence, the second stage filtered the technology and/or AI driven MNEs. Third, since the focus of our study is on DTMNEs, we followed previous empirical studies, such as Bouncken et al. (2021) and Trischler and Li-Ying (2022), in filtering our sample data to include only AI analytic and digital-driven global high-tech MNEs. Finally, we implemented strict data cleaning by removing outliers, deleting duplicate data and excluding inconsistent and missing information from our dataset. To ensure sample appropriateness, procedures were carefully conducted to rule out samples unrelated to AI digital-driven companies. Our final sample size, after cleaning the data and removing inconsistent data, was comprised of 56 DTMNEs whose BMs are driven by digital technologies.

3.2. Methodological approach

A consistent BM enhances firm performance and plays a decisive role in creating, delivering, and capturing firm value. However, during the

COVID-19 pandemic, several firms were forced into adjusting their BM rapidly, either by cutting or increasing their expenditure on R&D marketing costs, as well as their expenditure on patents, copyrights, and intangible assets etc. (Priyono et al., 2020; Clauss et al., 2021; Kraus et al., 2020b). Following Ritter and Pedersen (2020), we define the term 'digital BM drivers' in this study as BM (albeit with variables in the BM) for AI analytic and digital-driven companies.

Thus, in accordance with the extant literature (Priyono et al., 2020; Clauss et al., 2021; Kraus et al., 2020b; Ritter and Pedersen, 2020), we contend that, during the COVID-19 pandemic, decision-makers acted promptly on business performance, survivability, and solvency. As a result, the interaction among BM drivers, such as R&D, marketing expenses, intangible assets, capital expenditures, and ESG, has been critical in securing higher revenues and leveraging other financial opportunities. Chan et al. (2017) argued that identifying the relevant BM drivers can significantly impact firm performance and value, particularly during crisis periods.

Although previous empirical studies have used multivariate statistical analysis techniques, such as regression analysis (Huelsbeck et al., 2011; De Reuver et al., 2009), structural equation modelling (Bouwman et al., 2020), and confirmatory factor analysis (Hosni et al., 2018), among others, in examining BM and firm performance, analytical methodologies such as the structural equation modelling and confirmatory factor analysis were not suitable for our study due to the nature of our datasets. Instead, following studies such as Huelsbeck et al. (2011) and De Reuver (2009), we used linear regression as a baseline model in examining the association between the variables in our BM and firm performance. Our justification for using linear regression as our baseline is motivated by studies such as Chungyalpa et., al (2016) that argue that BM ontologies explains the value the company generate from its BM architecture. The value in this study refers to firm performance and the architecture embodies the key firm level factors including sales revenue (product and customers), management infrastructure and financial aspects (Chungyalpa et., al 2016). Wee operationalise the model by making firm performance (measured by return on assets) the dependent variable. The variables consisted of multiple independent factors (R&D expenses, market cost, ESG disclosure score, operational cashflow and intangible assets). Crisis periods create uncertainties and risk, therefore using multivariate linear regression enabled observation of how firm performance was affected by the unplanned changes of the variables in the firm's BM.

Also, although structural equation modelling (SEM) or confirmatory factor analysis (CFA) may be a suitable technique for this type of empirical analysis (Gallagher and Brown, 2013; Hosni et al., 2018), given the limited nature of data and research questions, we were unable to capture the required measurement indicators and latent constructs to operationalise these methodologies. To operationalise SEM and CFA, it is necessary to enter the intricate art of modelling both observed and unobserved variables (latent constructs), however, these were missing in our data. For example, SEM requires the use of appropriate measurement indicators based on a theoretical framework in constructing latent factors. SEM also involves the use of selected questionable instruments and multiple correlated predictors, as well as the use of variance and covariance to reflect the hypothesis to be tested. These processes are beyond the research scope and the data available for this study.

The selection of independent variables was guided by previous empirical studies, such as Chan et al. (2017) and Chaudhuri et al. (2016), who used R&D, marketing expenses, intangible assets, capital expenditures, and ESG as essential variables in determining firm performance. Despite the fact that these variables have been used in other studies, they are easily observable as BM drivers determining survivability, business continuity, and financial distress, which is relied on by business leaders (Breier et al., 2021; Chanyasak et al., 2021, Kraus et al., 2020b, and Priyono et al., 2020). For example, Breier et al. (2021); Chanyasak et al. (2021), Kraus et al. (2020b) and Priyono et al. (2020) argued that digitalisation, automation, big data analytics, AI, and digital-driven BM are seminal for business growth, survivability, and performance during COVID times. Further, previous empirical studies, such as Chan et al. (2017) and Chaudhuri et al. (2016), used similar variables in their study.

In line with these studies, we advance two broader perspectives for investigating whether the observed BM drivers contribute to firm performance and value creation in the sampled firms during the COVID-19 period. In the first perspective, we adopted four analytical approaches that investigate the association between each variable in the BM and firm performance from individual effects perspective. The other two analytical approaches, which rely on the PCA and MCDA methodologies, draw from the systems thinking approach. We used the aggregate composite index effect to investigate the effects between the aggregated composite index of the BM on firm performance and firm value during crisis periods. Overall, this paper examines BM drivers of our sampled DTMNEs using six different analytical approaches.

These six analytical thinking approaches are dependent on how the BM drivers (predictors) are empirically analysed (contribution to sales, asset efficiency, stress testing, composite indicators, elasticities, and so on) and their perspective (individual or multiple) in supporting decision-making. Please refer to our variable definition table (Table 1a) for the definition of the six different analytical approaches.

We operationalised the first analytical method using the traditional pooled OLS regression as a baseline and analysed the BM drivers and their association with firm performance based on accounting ratio predictions. We defined these as the accounting ratio model approach. In the second approach, we used a dichotomous variable to understand if the variables in the BM have recorded positive growth. This was the basis for investigating how a positive change in each variable in the BM affected firm performance and value. We define this as the growth rate approach model. In the third approach, we examined which of the variables in the BM have recorded a positive change using a dummy variable of 1 for a positive change, otherwise 0. We then used the model to investigate which variables influenced firm performance. We define this approach as the dummy of positive growth approach model.

Given that crisis periods produces uncertainties on BM, the fourth analytical approach followed the elasticity procedure. This approach examined how a unit change on each variable in the BM affected changes in sales revenue. We define this approach as the effort-strain or elasticity model. The fifth approach used The Principal Component Analysis (PCA) on BM drivers. This was done by undertaking an aggregated analysis to understand the variable that influenced the sampled firms' BM. The sixth approach utilised MCDA on BM drivers (i.e., aggregated quality). Therefore, while the first four approaches individually analyse the statistical significance of each of the variables in the BM, the last two (PCA and MCDA) used an aggregated composite index in analysing BM during crisis periods.

3.2.1. Th accounting ratio and growth rate approach

These two models (please refer to the variable definition Table 1a) relied on the traditional linear regression model in examining the association between the individual variables in the BM and firm performance. Previous studies using these linear approaches have yielded mixed results in both stable and unstable periods (Guney et al., 2020; and Chan et al., 2017). Interestingly, these previous empirical studies have used similar variables such as R&D expenses, marketing expenditures, intangible assets, capital expenditures, and ESG, among others, as part of their corpus of variables in examining predictors of firm performance or firm value (Guney et al., 2020; Chan et al., 2017). Our study contributes to the literature by contemporaneously examining the association between the variables in the BM and firm performance and firm value respectively from the context of DTMNE's during the

Table 1(a)
Variable definition table.

Variable name	Definition	Source
Firm-specific variables		
ROA	Operating income divided by total assets	Bloomberg database
R&D Expenditure	Research and Development Expense/Net Sales or Revenues	Bloomberg database
Intangibles	Non-identifiable assets including trademarks, patents, copyright, computer software etc.	Bloomberg database
Market Cost	Total operational cost associated with revenue generation.	Bloomberg database
CAPEX	Total capital expenditure for the period	Bloomberg database
ESG	Overall company environmental, social, and corporate governance disclosure score	Bloomberg database
Leverage	Total company debt divided by shareholders' equity	Bloomberg database
Cash Flow from operations	A proxy for operations efficiency is measured by total cashflow from operations for the period.	Bloomberg database
Tobin's Q	The ratio of the market value of a firm to the replacement value of the firm's assets	Bloomberg database
PCA composite index	The aggregate composite index represents the digital business model drivers measured by the eigenvalues and eigenvectors of a set of multiple variables or indicators which minimise the average squared distance from the inputs' data points to the best fitting line.	Author's construction
MCDA composite index	The MCDA composite index is measured by using an algorithm that (a) weights the individual business model drivers, (b) ranks them in order of comparative value creation abilities (priorities) and (c) provides an aggregate index that maximises the available information by simultaneously considering more than one indicator or criterion.	(Husain et al., 2021; Basile et al., 2021; Karam et al., 2020)
Business model Drivers Analytical Approaches		
The Accounting ratio approach	The predictors in the ratio forms approach represent the conservative approach to analysing a digital model using the traditional pooled OLS analysis.	Author's construction
The Growth rates approach	The predictors in growth rates approach captures variables in the business model that recorded positive (growth) changes during the crisis periods and the effects of these positive changes on firm performance and firm value.	Author's construction
The Dummy of positive growth approach	This measures the effects of a unit increase/decrease in each of the key variables in the business model in relation to firm performance and firm value. We give a value of 1 if a firm increased their financial figures on their business model drivers otherwise 0.	Author's construction
The Effort-strain or the Elasticity model	The elasticities approach measures the flexibility of moving or alternating variables in the business model during crisis periods and the elasticity of the change to sales (assuming sales revenue has been a key objective during crisis period). The FDBM allows flexibility in the product services mix in the business model to dynamically respond to uncertainties associated with crisis periods (adopted from Richter et., al., 2010; Evans and Bahrami 2020).	Author's construction
The PCA digital business model index	A model representing PCA aggregate composite index of the digital business model drivers during the crisis period	Author's construction
The MCDA digital business model index	A model representing the MCDA aggregate composite index of the digital business model drivers during the crisis period	Author's construction

***Note In this study, the term digital business model represents a business model for AI analytics and digital driven companies (Ritter and Pedersen, 2020). Hence, digital business model drivers in this study explains factors or variables in the business model that influences/drive firm performance and firm value. Also, in this study, our first 4 analytical models that examine business model without using aggregate composite index examine business model from individual firm perspective whereas the PCA and the MCDA examine business model from aggregate composite index perspective-For example the MCDA examines Business model from Pair-company comparisons perspective.

COVID-19 pandemic period.

We measure firm performance using return-on-assets (ROA[1]) as a proxy. We also used Tobin's Q (i.e., the ratio of the firm's market value to represent the value of the firm's assets) as a proxy to measure firm value. Thus, in this study, we provide empirical evidence that investigates the association between BM drivers, firm performance and value of DTMNEs during the COVID-19 pandemic using the traditional linear OLS regression approach. It is worth mentioning that, while the accounting ratios approach relies on historical financial statement information in predicting firm performance and value, the growth rate approach uses combinations of accounting and market information in predicting firm performance (Sirmon et al., 2011; Teece, 2007). In summary, the dependent variable for the regression model is represented as ROA_{it} for business performance and $Tobin's\ Q_{it}$ for valuation. $Tobin's\ Q_{it}$ is not shown across the equations for simplification purposes.

Whilst all BM drivers in the first regression model represent a ratio to total sales or total assets (see $BMDrivers_{it}$ in Eq. (1)), the BM drivers in the second regression model represents variations or growth rates (see $\Delta BMDrivers_{it-1}$ in Eq. (2)).

$$ROA_{it} = \beta_0 + \beta_i BMDrivers_{it} + \beta_k Controls_{it} + \varepsilon_i \quad \text{(Eq. 1)}$$

$$ROA_{it} = \beta_0 + \beta_i \Delta BMDrivers_{it} + \beta_k Controls_{it} + \varepsilon_i \quad \text{(Eq. 2)}$$

The practical managerial imperativeness of these two modelling perspectives (the accounting ratio and the growth rate approaches) is to demonstrate whether the variables in the BM explain firm performance during the COVID-19 pandemic periods. Given that most decision-makers were caught up in a quagmire of cost-cutting as well as moving and reallocating key resources simultaneously during the pandemic periods, our base argument hinges on the fact that analysing BM drivers separately would not fully reflect how companies managed and/or reorchestrated their resources during crisis periods. We argue that a more integrated approach that is based on an aggregated composite index would provide a better result in examining the linkages between BM drivers and firm performance and value rather than relying on the

[1] ROA is the ratio of EBITDA (earnings before interest, taxes, depreciation and amortization) to total assets.

simplistic traditional linear regression models.

3.2.2. The dummy of positive growth model approach

Following previous empirical studies, such as Hernandez-Perdomo et al. (2019); and Miyakawa et al. (2017), we use another approach that measures the effects of a unit increase/decrease in each of the key variables in the BM in relation to firm performance and value. Although this approach has not been further studied in the BM literature, we argue that during crisis periods such as the COVID-19 pandemic, decision-makers orchestrate (Yu et al., 2021) firm resources by considering the variables in their BM that provide positive growth and competitive advantage (Jatmiko et al., 2022). We operationalised the dummy of positive growth approach ($D\_BMDrivers_i$) by giving a value of one (1) to DTMNEs that increased their financial figures or the value of their BM drivers, and zero (0) otherwise. Since the baseline argument in this model is predicated on growth, we labelled this method as the Dummy of Positive Growth Model. We capture this model in equation (3) below.

$$ROA_{it} = \beta_0 + \beta_i D\_BMDrivers_{it} + \beta_k Controls_{it} + \varepsilon_i \quad \text{(Eq. 3)}$$

3.2.3. The effort-strain (stress-testing) or elasticity model

In the fifth approach, we introduced a proxy concept of stress testing the BM drivers based on elasticities in line with the work of Prasad (2010); and Desmet and Parente (2010). First, we observed that elasticity is widely used in the economics literature in analysing how market demand responds to price changes. Given that sales revenue represents a critical source of liquidity for business survival and continuity during crisis periods. We use the effort-strain or stress-testing model (elasticity model) in performing stress test on sales and used the result as a guide to investigating the elasticity of sales revenue as a result of changes in key variables in the business model such as market cost, R&D, among others. This approach has been extrapolated to other studies, for example, international trade (Bas et al., 2017; Rubini, 2014), in order to measure the strength of supply and demand as a result of tariffs and financial stability (Cihak, 2007). The same approach has also been used to determine the strength of credit as a result of interest and foreign exchange rates as well as in engineering science to measure an object's resistance (strain) when stress (effort) is applied (Zheng et al., 2008). Although, previous studies such as Zheng et al. (2008) argued that stress tests and scenarios analysis have become one of the strategies used by policy makers to attenuate the systematic risk associated with crisis periods, proxies of stress testing (elasticities) have not be used in examining BM drivers of DTMNE's during crisis period such as the COVID-19 pandemic.

Consequently, we have limited knowledge and understanding of the application of stress testing, in terms of elasticities or sensitivity analysis, to examine BM drivers' linkages on firm performance and value. For these reasons, we extend the literature by using the effort strain model (stress testing analytical model) to investigate which BM driver(s) provide positive value additions to firm performance. We use equations (4) and (5) below in operationalising the effort-strain (stress-testing model). Equation (4) examines the amount of effort decision makers must exert ($E\_BMDrivers_{it}$) to generate sales (Eq. (4)) during a crisis period. In other words, this indicator measures the *effort* (the strength) decision-makers are putting on BM drivers to enhance sales (strain).

$$E\_BMDrivers_{it} \equiv \frac{effort}{strain} = abs\left(\frac{\Delta BMDrivers_{it-1}/\Delta BMDrivers_{it}}{\Delta Sales_{it-1}/Sales_{it}}\right) \quad \text{(Eq. 4)}$$

$$ROA_{it} = \beta_0 + \beta_i E\_BMDrivers_{it} + \beta_k Controls_{it} + \varepsilon_i \quad \text{(Eq. 5)}$$

It is worth mentioning that using elasticities on individual BM drivers might not fully represent how companies managed or changed their BM to explain performance during crisis times. For example, we note that during crisis periods, decision-makers moved resources and variables simultaneously to survive. They also maximised opportunities to reduce the odds of bankruptcy during crisis periods.

3.2.4. Principal component analysis (PCA) model

The fifth approach relied on Principal Component Analysis (PCA) in examining variables that drive BM. The PCA process is typically used to obtain the degree of association between the principal components of all sets of BM drivers, by computing the eigenvalues and eigenvectors that minimise the average squared distance from the inputs' data points to the best fitting line (Gadekar et al., 2022; Chatterjee et al., 2022; Buffa et al., 2018). In other words, PCA methods are required to reduce the dimensionality of BM drivers such that most of the information in the data is preserved. It is important to emphasise that PCA differs from confirmatory factor analysis. While the first seeks to identify variables that are composites of the observed variables (BM drivers), the second assumes the existence of latent factors underlying the observed data without reducing dimensionality or preserving as much variability as possible in the aggregation. The main aim of using PCA, therefore, is to perform regression analysis (Eq. (6)) using the first main components of BM drivers. To the best of our knowledge, previous studies in BM have not dealt with the aggregation of BM drivers and firm performance using PCA because of a lack of observed data. However, recent studies in financial management have implemented PCA in regression models, such as Jiang et al. (2018), who studied different components of capital structure and financial performance, and Roy (2016), who explored multiple dimensions of corporate governance and firm valuation.

This research uses PCA to investigate the association between BM variables and firm performance and value during the COVID-19 pandemic period. Using the PCA, we were able to consider if the aggregated indicator ($PCA\_BMDrivers_{it}$) could better explain the linkages between BM drivers and firm performance and value as well as actions and decisions by policy-makers and mangers during the COVID-19 crisis period. Assuming that PCA is a consistent method to combine BM drivers, this would illustrate that decision-makers were moving all drivers simultaneously to respond to the rapidly changing business needs in the COVID-19 period.

$$ROA_{it} = \beta_0 + \beta_1 PCA\_BMDrivers_{it} + \beta_k Controls_{it} + \varepsilon_i \quad \text{(Eq. 6)}$$

3.2.5. MCDA on business model drivers (aggregated quality)

For the final approach, we recommend Multicriteria Decision Analysis (MCDA) to aggregate BM drivers. MCDA allows the introduction of a new view of systemic thinking by considering multiple attributes (Karam et al., 2020; Petkov et al., 2007) to describe, cluster, rank, and select options by simultaneously considering more than one indicator or criterion (Bouyssou et al., 2006). In analysing BM, some studies support MCDA applications in ranking strategies (Husain et al., 2021) whilst others support the selection of options (Basile et al., 2021).

This paper proposes the Preference Ranking Organisation Method for Enrichment Evaluations–PROMETHEE in line with the work of Brans and Mareschal (2005); Behzadian et al. (2010); De Keyser and Peeters (1996); and Guney et al. (2020) who determine an aggregate corporate governance index to explain firm performance. Similarly, this study uses PROMETHEE methods to aggregate BM drivers in an aggregated quality. Then, by implementing multivariate regression analysis, it is possible to determine its statistical significance to firm performance and value creation during the COVID-19 crisis. This aggregated quality, therefore, maximises the available information based on the selected criteria (BM drivers) and paired comparison (interdependencies) among DTMNEs. Our approach is consistent with Guney et al. (2020), who stated that scrutinising slight differences in resource redeployment and reutilisation among firms during crisis periods is critical in understanding their interrelationships or degree of dominance within industry ecosystems.

In practical terms, considering the data of 56 DTMNE's during the 2020 COVID-19 crisis period, we assume that BM drivers can be modelled using an outranking relationship[2] supported by the PROMETHEE methods. This has helped in defining the ideal values from the best companies based on the criteria measured by the elasticities comprising ratio effort-strain (Eq. (4)), to configure an aggregation function F for the set of m listed companies $a_i \in I$ $(I = 1,2, \ldots,m)$ as $g(a_i) = F[g_1(a_i), g_2(a_i), \ldots, g_n(a_i)]$ and n on multiple drivers (g_j). For instance, comparing company a (as a vector) with its peers x $(a, x \in A)$ from the technology industry s in year t, can be synthesised as follows:

$$AQ\_BMDrivers_s^t(a) = \frac{1}{(m-1)} \sum_{j=1}^{n} \sum_{\substack{x \in A \\ x \neq a}} \left[P_j(a,x) - P_j(x,a)\right]_s^t RI_j \qquad \text{(Eq. 7)}$$

Following the work of Rocco et al. (2016), we selected the generalised criterion (GC) type I strict or usual criterion $\left(F(x) = \begin{Bmatrix} 0 & x \leq 0 \\ 1 & x > 0 \end{Bmatrix}\right)$ that requires no additional parameter definition and allows identification of any difference between two companies, no matter how small the difference. Lastly, RI_j is a set of relative importance values (i.e., criteria weights used by Keller and Kirkwood (1999) over the selected BM drivers, where $\sum_{j=1}^{n} RI_n = 1, RI_n \geq 0$ and are assumed equally weighted.[3]

The final model for the multivariate regression model for firm performance can be shown as follows:

$$ROA_{it} = \beta_0 + \beta_1 AQ\_BMDrivers_{it} + \sum_{k=1} \gamma_k Controls_{it} \qquad \text{(Eq. 8)}$$

We aimed to determine whether a new multicriteria index provides more robust findings that would shed light on its role in firm performance during the COVID-19 period, using paired comparisons among AI- and digital-driven companies, and maximising the information captured by their BM drivers.

Finally, Fig. 1 summarises the proposed methodological framework, using multivariate regression analysis, to study the influence of BM drivers on firm performance (ROA_{it}) and valuation ($Tobin's\ Q_{it}$)[4] during the COVID-19 crisis. The proposed framework combines analytical or systemic thinking models, either from an individual decision-making perspective (separated drivers) or a multidimensional decision-making perspective (combined or aggregated drivers).

The dotted arrow in the centre of Fig. 1 provides four separate drivers which support individual decision-making perspectives, and where the regression models (equations (1)–(3) and (5)) are clenched. We looked for specific cause-effect relationships (statistical significance) in terms of firm performance and valuation which arose during the COVID-19 pandemic. The origin of the arrows relates to the BM drivers (independent variables) with the endpoint, the output or the dependent variable (performance and valuation). Similarly, below the dotted arrows are the aggregated drivers' approaches, supported by a multidimensional decision-making perspective. The regression models (equations (6) and (5)) encapsulate the systemic cause-effect relationships (statistical significance) in BM drivers and firm performance or valuation during the pandemic. In the same fashion, the origin of the arrows means the BM drivers (independent variables) which are now aggregated using PCA or MCDA (PROMETHEE methods).

It is, therefore, essential to mention that PCA or MCDA (PROMETHEE methods) are not interrelated and should not be confused with factor scores, ratings or rankings. While the first uses eigenvalues and eigenvectors to obtain the principal components of the BM drivers; the second uses pair-wised comparisons between companies to aggregate quantitative information from the BM drivers to obtain a new composite index (variable) for multivariate analysis, in line with other similar methodological approaches (Gadekar et al., 2022; Guney et al., 2020). Finally, the endpoint in Fig. 1 is the output or dependent variable. The findings of our work are discussed further below.

3.3. Test for robustness

Our results are robust and consistent across other regression approaches. First, following the Hausman test, the random effects/pooled Ordinary Least Squares (OLS) regression is discovered as a preferred option. As a result, we used pooled OLS regression as a baseline regression in testing our hypotheses. However, since exogeneity is a problematic assumption in the traditional linear OSL method, we proceeded to test for endogeneity problems in our models using the Three-Stage Least Squares (3SLS) as an alternative/comparative measure.

The 3SLS estimator is relatively more efficient in comparison to the Two-Stage Least Squares (2SLS) because it obtains instrumental variable estimates, considering the covariances across model error terms and simultaneous non-linear equations. There are two main reasons for using the 3SLS regression model. First, the 3SLS model has an additional step to the 2SLS in dealing with endogeneity problems. Thus, after the 2SLS estimate which provides the correlation between the error terms in each equation, the 3SLS use this information to compute a feasible generalised least squares (FGLS) estimator. The FGLS estimator is more efficient than equation-by-equation 2SLS. Second, the 2SLS is typically referred to as a "limited information" model estimation while the 3SLS comparatively considered the additional information contained in the correlation of the error terms in each equation (Gretz and Malshe, 2019; Greene, 2018). In addition to this, all our results passed the variance inflation (VIF) test. Hence, overall, our results are robust to alternative measures, sample selection problems, multicollinearity, and potential endogeneity.

4. Findings

4.1. Descriptive statistics

Tables 1(a) and 1(b) represent the variable description and summary statistics of the study, while Table 2 shows the pairwise correlation matrix of the corpus of variables used. In this study, the term digital BM represents DTMNEs whose BMs are driven by AI analytics and digital innovation. Hence, digital BM drivers in this study represent the variables in the BM of DTMNE's that influence/drive firm performance and firm value. The burgeoning work done in this line of research on BM includes (a) a value creation model (Yunus et al., 2010), (b) a strategy for increasing sales and resources orchestration (McGrath, 2010) and (c) a system that solves a business problem using big data accumulation, data analysis including algorithms, AI and machine learning (Massa et al., 2017).

Our results, as set out in the summary statistics table, show approximately 8.1% return on assets (ROA) and a 2.2 Tobin's Q mean measure. These figures suggest that, on average, the DTMNEs in our sample generated positive returns during the COVID-19 pandemic. Also, the total market cost of these firms averaged approximately 7.3% of total expenditure. Meanwhile, R&D expenditure and capital expenditure of these firms represented a disappointing 5% and 7% respectively. On the contrary, we recorded a mean value of approximately 26% in ESG, which implies these firms are taking their ESG commitments seriously, and although our sampled DTMNE's are not meeting their

[2] The outranking relationship, denoted as S, does not determine if the relationship between two alternatives a and b is a strong preference (aPb), weak preference (aQb), or indifferent (aIb), but instead establishes if "the alternative a is at least as good as the alternative b" (Brans and Mareschal, 2005).

[3] Other GC types and RI might be used. However, they require additional information from decision makers. We thus consider the GC "type I″ and RI equally since no additional information is required in the same way it is proposed by Guney et al. (2020) and Rocco et al. (2016). Further research regarding other types of GC and different IR for BM drivers needs to be developed considering that this might impact on the statistical significance and explanatory power of the regression models.

[4] For firm valuation (value creation), substitute in the regression models ROA_{it} by $Tobin's\ Q_{it}$

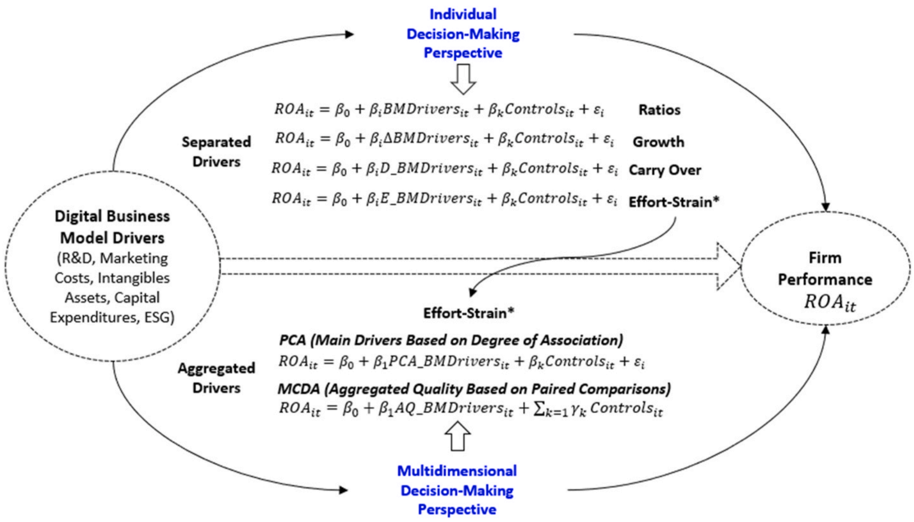

Fig. 1. Methodological framework on business model drivers and firm performance.

Table 1b
Descriptive statistics.

Variable	Minimum	Maximum	Mean	Standard Dev	P25	Median	P75	kurtosis
ROA	0.959	19.139	8.131	4.568	4.877	7.750	10.597	2.882
R&D/sales	0.000	0.077	0.005	0.012	0.000	0.001	0.003	25.097
Intangibles	0.000	0.447	0.083	0.105	0.015	0.043	0.087	6.155
Market Cost	0.408	0.901	0.726	0.099	0.707	0.746	0.785	4.202
CAPEX	0.000	0.110	0.007	0.019	0.000	0.001	0.006	20.468
ESG	0.124	0.554	0.257	0.122	0.174	0.215	0.306	3.133
Leverage	0.000	0.224	0.193	0.302	0.070	0.164	0.231	0.964
Cash Flow	−0.195	0.407	0.101	0.074	0.070	0.090	0.132	10.817
Tobin's Q	0.696	8.621	2.188	1.554	1.310	1.764	2.329	9.343
PCA	−0.239	0.538	−0.013	0.091	−0.033	−0.025	−0.015	26.181
MCDA index	−0.618	0.869	0.006	0.383	−0.284	−0.069	0.327	2.258

Table 2
Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) ROA	1.000										
(2) R&D	−0,245	1.000									
(3) Intangibles	−0.195	−0.041	1.000								
(4) Market cost	−0.415[a]	−0.337[a]	0.031	1.000							
(5) CAPEX	−0.42	0.272[a]	−0.013	−0.296[a]	1.000						
(6) ESG	−0.056	0.157	0.294[a]	0.106	−0.251	1.000					
(7) Leverage	−0.276[a]	0.322[a]	0.488[a]	0.192	−0.095	0.281[a]	1.000				
(8) Cash flow	0.267[a]	0.500[a]	0.050	−0.485[a]	−0.253	0.182	0.184	1.000			
(9) Tobin's Q	0.679[a]	−0.010	−0.198	−0.545[a]	0.335[a]	−0.171	−0.166	0.231	1.000		
(10) PCA	−0.065	0.612[a]	0.013	−0.158	−0.019	0.056	0.322[a]	0.576[a]	−0.112	1.000	
(11) MCDA	−0.283[a]	−0.044	−0.190	0.160	0.153	0.006	−0.055	−0.035	−0.194	0.037	1.000

[a] Shows significance at the 0.05 level.

environmental expectations, they are likely to be doing something well in the areas of governance and or social commitment. We also noted an average cash flow of 10% and average leverage of 19%. These values imply that sampled DTMNEs were still able to generate cash from operations (albeit relatively insignificant) during the COVID-19 crisis. Further, approximately 19% of their assets were owned by outsiders or third-party firms and used as a strategic shield for offshoring, near-shoring, near-sourcing, reshoring and competitive posturing (Adams et al., 2018). Table 2 shows the pairwise correlation among the corpus of variables used in our analysis.

4.2. Empirical results

We operationalised our hypotheses testing using two broad approaches. The first approach focused on the four analytical models in our study that examine BM drivers from a unitary (individual variable effect) perspective, while the second approach examined the BM drivers from an aggregated composite index perspective. Thus, we test the first three hypotheses using our four statistical models (a) the accounting ratio model, (b) the growth rates approach model, (c) the dummy of positive growth model, and (d) the elasticity/stress testing approach model. Given that firms deploy different strategic resources mix during times of uncertainty to secure business continuity and growth, we applied an aggregate perspective of the BM drivers using the PCA and the MCDA model. Thus, these two models allow us to examine if the aggregated information (variability or pair-wise comparisons) can provide a more consistent relationship between the variables in the BM and firm performance during crisis periods.

4.2.1. *The relationship between operational cashflow and firm performance and value during crisis periods*

We use our results in Tables 3(a) and 3(b) in testing hypothesis 1. Our findings from Tables 3(a) and 3(b) used accounting ratios and growth rate model analysis, respectively, in predicting the association between cashflow from operations and firm performance and value. First, we observed mixed findings between cashflow from operations (CFOP) and firm performance (FP) and firm value (FV) using the accounting ratio (which showed a negative association between CFOP and FP) and the growth rate approaches which provided both negative and positive approaches between CFOP and FP and FV). However, we recorded a significant positive linkage between CFOP and firm FP using the elasticity approach model and the stress testing (efforts strain on sales model) approach in Tables 4a and 4b. These observations imply that during the COVID-19 period, decision-makers were concerned about the effects of unitary changes (elasticities) of each BM driver on firm performance and value rather than the accounting ratio predictions. Thus, in crisis periods, management should carefully examine which driver positively impacts firm performance by critically subjecting each variable in their BM to stress testing, particularly cashflow from operations and sales, which is statistically significant.

Our findings are consistent with previous studies, such as Dickinson (2011), who argued that business constraints make BM challenging to examine during unstable periods. Cressy (1996) and Dickinson (2011) implied that operating cash flows represent one of the critical components of a BM, used as a proxy in measuring a firm's operational efficiency and lifecycle. Additionally, studies such as Almamy et al. (2016) argued that cash flow is an essential predictor of corporate solvency; hence decision-makers need to critically examine cash flows during crisis periods. Our results extend the literature by providing empirical evidence that supports the benefits of using the efforts strain on sales model (stress testing approach) and the elasticity analytical procedures in examining cash flow from operations during crisis periods.

4.2.2. *The relationship between R&D expenditure and firm performance and value during crisis periods*

Extending Massa et al. (2017) work, we argue that a BM should seek to explain how value is created with regard to a firm's product and services innovation capabilities and software technology management, as well as how value is captured through timely resource reconfigurations. To justify this aspect of our work and to test hypothesis 2, we included the R&D variable in Tables 3 and 4 as a proxy for measuring DTMNE'' innovation capabilities. The accounting ratio approach results reveal a statistically significant association between R&D and FP and similar results between R&D and FV. On the contrary, our findings using the growth rate procedure reveal a positive but insignificant association between R&D FP and a negative association between R&D and FV. These two results again confirm the inconsistencies associated with using individual approaches in examining variables in BM. Interestingly, when we introduced the elasticity and the stress testing proxy in Table 4, we noted that although it is not statistically significant, as expected, there is a positive linkage between R&D and firm performance and a consistent positive association between R&D and firm value (see Tables 4a and 4b).

Our findings have important managerial and practical implications. First, our results again highlight the limitations of using the traditional accounting ratios approaches in examining BM drivers. For instance, our results in Table 3 suggest that using accounting-based ratios in determining the potential linkages between variables associated with BM and firm performance, particularly during the COVID-19 period, provided inconclusive results. Second, our result is consistent with previous studies such as Zott et al. (2011) and Mason and Mouzas (2012) who implied that to achieve superior financial performance and value, firms must invest in appropriate R&D that meets the changing needs of customers, especially during crisis periods. However, to identify which areas to invest in, firms need to adopt an analytical approach that can identify appropriate innovations that provide positive growth and firm value. Investing in new technologies, such as artificial intelligence, digitalisation, automation, and machine learning, among others, can provide competitive advantages to firms during periods of high uncertainty (Kim and Park, 2021; Sjödin et al., 2021).

Table 3
(a and b).

VARIABLES	(a) The Accounting ratios approach				(b) Th Growth rates approach			
	Firm Performance		Firm Value		Firm Performance		Firm Value	
	OLS	3SLS	OLS	3SLS	OLS	3SLS	OLS	3SLS
R&D	−14.903**	−26.268***	−3.481*	−8.227***	0.002	0.478*	−0.002	−0.002
	(6.965)	(8.285)	(1.685)	(30.184)	(0.043)	(0.930)	(0.015)	(0.013)
Intangibles Assets	−3.294	−16.372**	−2.899*	−6.797**	0.547	9.957**	−0.751	−0.751
	(5.079)	(8.074)	(1.567)	(2.939)	(1.697)	(22.204)	(0.567)	(0.519)
Market cost	−6.454	−71.622***	−3.776*	−27.549***	−10.566	−1203.589	0.272	0.272
	(6.395)	(23.750)	(1.982)	(10.009)	(15.420)	(2012.827)	(5.268)	(4.826)
Capex	−28.974	−85.557	34.301***	−6.586	0.586	0.454	−0.058	−0.058
	(33.539)	(68.613)	(9.520)	(27.245)	(0.366)	(3.833)	(0.128)	(0.117)
ESG disclosure	−1.752	−2.347	−1.416	−1.103	−14.565**	−15.947	6.919***	6.919***
	(3.968)	(6.463)	(1.248)	(2.333)	(6.546)	(2.383)	(2.111)	(1.934)
Leverage	−0.007	0.069*	0.012**	0.035**	7.928*	26.999**	1.445	1.445
	(0.019)	(0.037)	(0.006)	(0.014)	(6.819)	(256.917)	(2.342)	(2.145)
Cash flow from operation	15.500	−17.008	4.805	−8.732	1.961***			
	(10.018)	(24.599)	(3.192)	(9.990)	(0.320)			
Tobin's Q	1.619***				−0.026*	−0.288	−0.002	−0.002
	(0.393)				(0.016)	(0.424)	(0.005)	(0.005)
ROA			0.164***				0.227***	0.227***
			(0.040)				(0.037)	(0.034)
Constant	9.493*	64.485***	3.431**	23.713***	3.663***	21.135	0.056	0.056
	(5.544)	(19.263)	(1.748)	(8.108)	(0.953)	(25.672)	(0.371)	(0.340)
Observations	56	56	56	56	56	56	56	56
R-squared	0.521	0.532	0.587	0.498	0.519	0.521	0.534	0.513

The traditional digital model represents the conservative approach in analysing a digital model using the traditional pooled OLS analysis. The change digital business model measures the effects of the changes in each variable on firm performance and firm value. The standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4
(a and b).

VARIABLES	(a) Dummy of positive growth Approach				(b) Effort-strain on sales (elasticities)			
	Firm Performance		Firm Value		Firm Performance		Firm Value	
	OLS	3SLS	OLS	3SLS	OLS	3SLS	OLS	3SLS
R&D/Sales	0.185	0.185	0.042	0.042	0.018	0.021	0.021	0.022
	(0.975)	(0.893)	(0.333)	(0.305)	(0.002)	(0.002)	(0.001)	(0.001)
Intangible Assets	1.199	1.199	−1.114**	−1.114**	−0.005	−0.005	−0.038	−0.038
	(1.518)	(1.391)	(0.496)	(0.455)	(0.170)	(0.155)	(0.060)	(0.055)
Market cost	0.810*	0.810*	0.231	0.231	0.038	0.038	−0.365	−0.365*
	(0.990)	(0.907)	(0.339)	(0.311)	(0.675)	(0.619)	(0.232)	(0.213)
Capex	−1.030	−1.030	0.138	0.138	0.019	0.019	0.004	0.004
	(1.038)	(0.951)	(0.358)	(0.328)	(0.021)	(0.019)	(0.007)	(0.007)
ESG Disclosure	10.314*	10.314*	0.763*	0.763*	−0.469*	−0.469*	0.184*	0.184**
	(6.745)	(6.179)	(2.359)	(2.161)	(0.276)	(0.253)	(0.097)	(0.089)
Cash flow from operations	2.255*	2.255*	1.424	1.424	11.813*	11.813**	1.020*	1.020*
	(4.182)	(3.832)	(1.419)	(1.300)	(6.531)	(5.983)	(2.381)	(2.181)
Leverage	−0.035**	−0.035**	0.001	0.001	−0.035**	−0.035**	0.001	0.001
	(0.017)	(0.015)	(0.006)	(0.005)	(0.016)	(0.015)	(0.006)	(0.005)
Tobin's Q	1.788***	1.788***			1.777***	1.777***		
	(0.338)	(0.309)			(0.321)	(0.295)		
ROA			0.209***	0.209***			0.222***	0.222***
			(0.039)	(0.036)			(0.040)	(0.037)
Constant	2.122	2.122	1.549**	1.549**	4.273***	4.273***	0.549	0.549
	(2.044)	(1.873)	(0.670)	(0.613)	(1.275)	(1.168)	(0.495)	(0.453)
Observations	56	56	56	56	56	56	56	56
R-squared	0.587	0.583	0.602	0.586	0.582	0.584	0.576	0.585

Please note: The flexible digital business model measures the flexibility of moving or alternating variables in the business model during crisis periods and the elasticity of the change to sales (assuming sales revenue has been a key objective during crisis period). The dummy digital business model measures the effects of a unit increase/decrease in each of the key variables in the business model on firm performance and firm value. The Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.2.3. The association between efforts strain on sales (elasticity) and firm performance and value during crisis periods

Although increasing sales and revenues is one of the key objectives of most firms, during crisis periods these levers are affected by uncertainty. Consequently, using sales as a common denominator, we investigated the association between the variables in the BM relative to firm performance during crisis periods by utilising the efforts-strain model or the stress testing approach. We operationalised this by including another variable in the analysis (see Table 4(b)) to investigate the consistency in our modelling results. Consequently, we transformed all our explanatory variables following elasticity analyses. We used the concept f elasticity for stress testing using the changes in sales as a denominator, in line with the work of Prasad (2010) and Desmet and Parente (2010), who argued that increasing sales is a critical factor during an economic crisis.

Our results in Table 4 revealed a significant positive association between cash flow from operations and firm performance. Also, we noted a significant positive association between return on assets and firm value and a significant positive association between R&D and firm performance. Nonetheless, while these results are encouraging, we noted inconsistent results between the other variables in our BM and FP and FV. These findings suggest that, although the elasticity stress testing and growth rate approaches are consistent, from an individual firm-level and internal factors perspective, they may in some instances be limited in providing a better understanding of which variables drives firm performance during the crisis period. Other studies, such as Lee et al. (2019); and Mousavi and Lin (2020) implied that crisis periods entail complex internal and external factors, so decision makers need to take into consideration multiple factors (from both internal and external sources) in taking strategic decisions. Additionally, Lee et al. (2019) contended that decision-makers require a multidimensional approach in dealing with the complex smokescreen challenges associated with crisis periods. Other previous empirical studies imply that to facilitate business continuity and growth during crisis periods, decision-makers must examine their BM from holistic/macro perspective rather than focusing on individual factors that drives growth and value (Lee et al., 2019; Pereira et al., 2021; Mousavi and Lin, 2020). Against the above backdrop, we argue that methods such as PCA, SEM PLS and MCDA will offer a better result when examining or aggregating variables around BM.

4.2.4. Relationship between the MCDA composite index and firm performance and value during crisis periods

Strategic business decisions, particularly during crisis periods, are complex and multifaceted and require a higher degree of caution. We argue that analytical procedures that rely on an aggregated index, such as PCA and MCDA, could provide more consistent and better explanations about the linkages between variables in the BM and firm performance and value during crisis periods (Mousavi and Lin, 2020). Thus, relying on statistical approaches that focus on individual BM drivers/predictors, such as those used in our first four analytical approaches in Tables 3 and 4, may be limited. Therefore, in testing hypothesis 4, we used the aggregated index method that includes (a) The PCA vector (the principal component of BM drivers) and (b) the MCDA composite index (PROMETHEE methods).

It is worth mentioning that the PCA method reduces the dimensionality of the multiple BM drivers creating a new non-correlated variable, which maximises variance and considers resource allocation within the firm. Alternatively, the MCDA approach using the PRMETHEE methods uses pair comparisons to relatively compare resource allocation among peer companies around AI and IT-driven activities. The aggregated MCDA index helps determine how intensely a firm is allocating its resources during the pandemic period concerning its rival companies versus how the competitors are relatively analysing this firm. From our perspective, the PCA and MCDA adopt a systematic analysis that can minimise managerial decision-making biases.

Our results in Table 5 show that, unlike the previous four approaches, examining BM drivers using the MCDA composite index provides a more consistent and better explanation about the linkages between BM drivers and firm performance. Our result from Table 5, therefore, confirms hypothesis 4. Compared to our first four models that provided mixed and inconclusive results, the MCDA approach shows a negative association between the composite index and firm performance (FP) and firm value (FV) during the COVID-19 pandemic period. This observed association elucidates that a negative result can be achieved if firms quickly invested or moved resources across different operational

Table 5
(a and b): A multi-criteria decision approach (MCDA) business model and Principal component approach (PCA) Business model
(a) The PCA on business model drivers (b) MCDA on business model drivers.

VARIABLES	Firm Performance		Firm Value		Firm Performance		Firm Value	
	OLS	3SLS	OLS	3SLS	OLS	3SLS	OLS	3SLS
Composite DBM index	−2.238	−2.337	−2.685	−2.887	−2.133**	−2.133**	−0.013	−0.013
	−6.443	−6.546	−2.231	−2.129	(1.156)	(1.103)	(0.440)	(0.420)
leverage	−0.029*	−0.039**	0.002	0.002	−0.033**	−0.033**	0.000	0.000
	−0.015	−0.025	−0.006	−0.005	(0.015)	(0.014)	(0.006)	(0.005)
Cash flow from operations	10.884	11.864	3.158	3.197	10.600**	10.600**	1.083	1.083
	−7.960	−7.896	−2.824	−2.645	(6.204)	(5.920)	(2.346)	(2.239)
Tobin's Q	1.652***	1.753***			1.668***	1.668***		
	−0.314	−0.299			(0.300)	(0.286)		
ROA			0.217***	0.227***			0.227***	0.227***
			−0.039	−0.027			(0.041)	(0.039)
Constant	3.527***	3.628***	0.032	0.034	4.057***	4.057***	0.229	0.229
	−1.045	−0.997	−0.408	−0.390	(0.930)	(0.887)	(0.400)	(0.382)
Observations	56	56	56	56	56	56	56	56
R-squared	0.514	0.568	0.488	0.530	0.689	0.645	0.654	0.624

Please note composite DBM index represents composite digital business model drivers which comprise (a) the MCDA digital business model index and the PCA digital business model index. The standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

and strategic units during crisis period without considering key composite aggregated factors in their BM. In other words, by using the MCDA composite index, based on the PROMETHEE methods, our pair-wise-company comparison results suggest that when firms from our dataset rapidly moved their resources across different operations during the pandemic, we recorded a negative firm performance and value.

Our findings complement other studies, such as Shen et al. (2020), who implied that most firms faced revenue constraints during the pandemic. As a result, business leaders that took hasty decisions without considering company factors and functional interrelationships, for example, competitive edge, customer perception, supply chain constraints, and managerial distress, suffered poor performance and potential collapse. Similar results were discovered by Siagian et al. (2021). Also, studies such as Amaral and Costa (2014) argued that making decisions in crisis periods is a complex process that requires critical thinking and strategically rationalising choices. We argue that decision-makers should analyse and eliminate bottlenecks that stifle growth and allocate key resources more efficiently during crisis periods. It is worth mentioning, as a limitation of this study, that similar to other linear regression models, our analysis and results were based on linear assumptions, and hence a meticulous study is needed to examine the variables in BM that can secure better organisational outcomes. MCDA composite index, compared to the previous five analytical approaches, is a better alternative to rank and determine a firm's relative position concerning its peers and vice versa. MCDA can provide a quick guide for decision-makers in crisis periods regarding investment, asset allocation, and portfolio management (Mousavi and Lin, 2020; Li et al., 2021; Settembre-Blundo et al., 2021; Guney et al., 2020). Our study underscores the importance of the use of algorithms, AI, bigdata analytics, machine learning etc. to guide strategic decisions during crisis periods.

5. Discussions and conclusions

This study draws from the resource orchestration theory to critically examine how decision-makers can benefit from the use of AI analytics and digital technology to achieve better firm performance and value creation, particularly during crisis periods. Most companies are contemporaneously faced with the challenges of identifying which components of their BM drive maximum performance as well as how to allocate scarce resources during crisis periods. Since companies operate as a system, examining BM from the individual effect perspective has largely produced inconclusive results. Rather, using digital technologies, including AI analytics, and machine learning algorithms in allocating resources appropriately during crisis periods, can yield better firm performance and value. We have highlighted that using the first four traditional linear approaches (please refer to the variables definition table) not only produces inconclusive results but also provides a limited perspective to the BM drivers (variables in the BM that influence firm performance).

Thus, the first four approaches consider BM drivers by considering the internal organisational factors, with little or no attention to the external factors, such as competitive edge, customer perception, supply chain constraints and managerial distress. In providing a reliable perspective about which variables in the BM drive firm performance and value, we argue that using the aggregated composite index approach, such as the MCDA index, provides more consistent results as well as a better picture of how a firm needs to reallocate its resources during the crisis period to achieve better performance and value. Also, the aggregated composite index approach which uses digital technologies, such as AI analytics and machine learning, can provide a better perspective regarding how MNEs perform in comparison to their rivals during crisis periods.

This can help business leaders understand the strategic typologies within industry ecosystems for effective re-strategising in order to maximise business continuity and sustain a competitive edge. From the perspective of this study, the PCA and MCDA, unlike the first four traditional linear approaches, comparatively use better algorithms that can minimise managerial decision-making biases. Our findings imply that to achieve business continuity during crisis periods, BM should be driven by digital technologies (Kimani et al., 2020; Leone et al., 2022; Chirumalla, 2021).

Innovation protagonists, such as Zott et al. (2011); Amit and Zott (2015), have confirmed the relationship between BM design as an assurance for firm profitability. Similar to the resource orchestration supporters, the contrasting conversations around BM seem to have left out the element of resource re-orchestration as a key part of the business continuity strategy for (a) remaining a going concern, and (b) responding to uncertainties in highly contested markets that are fragile because of unplanned and unexpected crisis.

Our study, therefore, has attempted to bridge these gaps by questioning how successful firms create a BM that is financially sustainable by responding to requirements of remaining as a 'going concern' while also remaining flexible and agile in responding to different unpredictable crises situations such as the COVID-19 pandemic, using their available resources. To answer this question, understand managerial behaviours during crisis periods, and contribute to theory and managerial practice, we have drawn on some traditional precepts from six dimensions, including independent driver analysis, growth perspectives, classification analysis, principal component analysis (PCA), MDCA and elasticities (consisting of effort and/or strength).

In our findings, we have logically demonstrated how the MCDA composite index can provide critical insight into key BM drivers, why resource re-orchestration is needed, as well as the effects of both of these factors on financial performance and firm value during crisis periods, such as the COVID-19 pandemic. Our result is consistent with the two streams of theories which forms the basis of our analysis, including the resources orchestration argument and BM innovation. More importantly, the central thesis that congeals our arguments together is hinged on the fact that to achieve optimal financial performance during crisis periods, a fir''s resource re-orchestration endeavours should cover at least three key areas including (1) breadth (i.e., resource orchestration across the scope of the firm), (2) lifecycle (i.e., resource orchestration at various stages of the firm's maturity), and (3) depth (i.e., resource orchestration across levels of the firm). The findings, as demonstrated in Tables 3–5, confirm the results of the analytical approaches adopted for this study. As stated previously, BM innovation literature is yet to show how top DTMNEs can re-think their BM by redefining what they do, as well as how, when and where they do it (Jovanovic et al., 2021; Kraus et al., 2020a; Leminen et al., 2020; Latifi et al., 2021). Essentially, the concepts of agility and ambidexterity show managerial ability to unlearn and re-learn, to respond, adjust and adapt to changes in dynamic contexts and business environments. Finally, the proposed MCDA approach, based on the PROMETHEE methods, reveals a new and fundamental path to analyse the link between BM drivers and firm performance and valuation. Moreover, it overcomes the limitations of analysing the drivers independently, which traditionally fails to detect and scrutinise small differences among companies regarding their BM drivers.

5.1. Theoretical implications

Based on resource orchestration theory, our research uses a novel MCDA approach to highlight how firms can orchestrate resource-related activities during a crisis. To re-orchestrate resources effectively during crises, decision-makers are especially interested in understanding which components in their BM can provide better strategic benefits to their financial performance and value. The magnitudes of these variables and the flexibility or degree of freedom in choosing between alternative variables are even more crucial. During crisis periods, directors could consider reconfiguring firm resources and activities to minimise inefficiencies/costs and maximise efficiencies/profits by stress-testing their models against MCDA, supported by PROMETHEE methods.

Resources optimisation to achieve business continuity, plasticity and understanding the dynamics of BM is nascent but of theoretical and practical importance. Our study adopts a systematic approach in using different statistical methods to analyse BM under crises to provide a more comprehensive picture of how BM for DTMNEs can be changed. The method used in this study highlights the significance of analysing BM holistically rather than doing so in individual forms. Therefore, our novel MCDA approach also provides a tool for future strategic management and related studies using resource orchestration theory to explore or evaluate resource reconfiguration in a wider context to gain holistic perspectives on corporate decision-making during crises.

Finally, although both methodological and theoretical contributions might overlap, MCDA provides an additional framework for interpreting patterns and reducing discrepancies around resource orchestration theory during crisis times. In particular, MCDA helps connect variables providing a better description and explanation for BM drivers and firm performance.

5.2. Practical implications

The results obtained from the MCDA approach have led to interesting and robust findings and practical implications. Firstly, the study provides fresh evidence of the aggregate quality of BM drivers and provides an adequate explanation of the factors influencing firm performance during crisis periods, particularly, to conduct industry analysis, peer comparison and competitive analysis, or benchmark studies. Our MCDA findings are statistically significant and demonstrate a better way to understand how firms re-orchestrate resources using multiple decision points to remain agile during crises periods. Consequently, this aggregated quality can be included in portfolio management (company selection, prioritisation, and investment allocation) and resource configuration theory to better understand the business dynamics, industry structure and competitive landscape in line with Sirmon et al. (2011). Secondly, while burgeoning scholarly work dealing with asset management and resource orchestration is nascent, our findings provide guidelines as to how firms can maintain competitive advantage in post-crisis periods (outperforming companies, weak competitors, and firms with superior margins compared to market rivals). It also means that machines and AI cannot replace the managerial effort and strength of the human resource capabilities/competencies, given that resource re-orchestration needs managerial inputs (actions and decisions). Thus, the way in which managers analyse sensitivity or elasticity approaches (i.e., amount of firm's efforts to sale or deliver services better than its competitors) stress tests and orchestrate the breadth of resources at the firm's disposal will determine the likelihood of achieving competitive advantage during and post-crisis periods (Sirmon et al., 2011; Sirmon et al., 2008; Wendt et al., 2022).

Finally, our multidimensional approach reveals that the effect of the aggregated index of BM drivers obtained is negatively associated with firm performance. This implies that having a higher level of compliance and cash flow burden around BM drivers can reduce profitability due to associated costs. In order words, creating value and developing competitive advantages requires flexible approaches to balancing financial and non-financial variables, which are highly related to resource orchestration and synchronisation processes (Sirmon et al., 2007; Kraus et al., 2020a; Leminen et al., 2020).

5.3. Limitations

This empirical research is supported by the resource orchestration theory, elevating the critical importance of BMI and digitalisation as means to help companies remain agile, especially during crisis periods, and consequently, create long-term value for internal and external stakeholders. However, the methodology and results rely on a sample of technology MNEs that are heavily investing in digitalisation, automation, and artificial intelligence. Hence, other companies and sectors will require further analysis and investigation to extrapolate the conclusion and findings of this study. Additionally, it is worth mentioning that this study only takes into account the COVID-19 pandemic period between January 2020 and December 2020. Whilst the data is based on the COVID-19 crisis period, the findings and analysis does not consider issues outside of this timeline. However, the implications could be relevant in understanding how firms re-organise resources during similar crises to sustain performance and improve value. It is important to note that this paper does not intend to compromise the current practices of scrutinising companies for investment purposes. Instead, our primary goal is to contribute to the existing literature on BM and to bring insight to decision-making strategies during the COVID-19 crisis from a multidimensional business perspective (ratio analysis, growth measures, carry-on detection, effort-strain, principal drivers' components and aggregated quality). Therefore, the study allows for extending the MCDA application and analysis of BM drivers during crisis periods.

The process of comparison to obtain the aggregate quality of BM drivers is drawn from technology MNEs. Other circumstances (i.e., law, regulations, new drivers or sector-related dynamics) can relatively skew the preference of one model over the other business drivers. However, the PROMETHEE (MCDA) and PCA methods provide sensitivity analysis for business drivers using multivariate and regression analysis to weigh the extent of resource re-orchestration required to remain agile and successful during crisis periods (Ramli et al., 2011; Guney et al., 2020). It is important to indicate that other techniques for robustness analysis, as used by Simon et al. (2013), are out of the scope of this paper. Finally, it is better to focus on firm resource orchestration perspective (Pfeffer and Salancik, 2003) to understand why some firms remain agile, whilst others fail after a major crisis.

5.4. Conclusion and areas for future research

The main objective of this study has been to explore how incumbent DTMNEs re-deploy existing key resources to reconstruct, re-capture and deliver value during times of crises and uncertainties, following the works of Kimani et al. (2020) and Jovanovic et al. (2021). The most important line of argumentation in this paper is that indiscernible challenges and market uncertainties, such as those experienced during the 2020 pandemic crisis, could be better understood and managed by directors of businesses if they can foster business continuity and resilience by using the appropriate analytical tools to identify key BM drivers (Pereira et al., 2021; Kraus et al., 2020b; Wendt et al., 2022). Thus, the conceptualisation of business agility and plasticity during crisis periods, which are missing in previous studies, are captured in the individual and composite analytical approaches used in this study to evaluate the resilience of BM on one hand, and resource re-orchestration on the other. These findings may be applied in combination with other practical toolkits, see e.g Bouwman et al. (2020).

Our findings broadly imply that a firm's innovative ability, cash flow from operations, revenue generation abilities and operational efficiency are key value-creation drivers during the pandemic crisis. Consequently, we, present our primary findings/contribution based on the issues identified and presented in Fig. 1 by showing that multidimensional decision-making perspectives enhance holistic analyses during crisis periods. Additionally, DTMNEs that heavily invest and seek to enhance their businesses around digitalisation, automation, and artificial intelligence could minimise loss of firm value by using a multi-strategic lens to remain agile. BM model approaches have not been implemented before in examining the BM drivers of DTMNEs during crisis periods. Thus, our study offers insights to managers and decision-makers about which analytical BM approach is appropriate for examining firm performance and value creation during crisis periods. This research focuses attention on business drivers (e.g., R&D, marketing expenditures, intangibles, ESG, among others) and explores different angles to determine their significance during the atypical business turmoil of COVID-19. It relies on contribution analysis (ratio analysis), growth drivers and measures, carry-on detection (dummy variables), effort-strain (elasticities), main drivers such as components (PCA analysis), and aggregated quality (MCDA applications). Therefore, future studies could investigate how our sample MNEs re-adapted their strategies through resource orchestration post-COVID-19 pandemic.

Although our study supports all the analysis and conclusions using multivariate regression analysis, further research needs to consider implementing structural equation modelling and confirmatory factor analysis (Gallagher and Brown, 2013). These techniques can model both observed variables (BM drivers) and unobserved variables (i.e., leadership, IT disruption, and business diversification) linked to other theoretical constructs. The multivariate statistical methods can be complemented by the heterotrait-monotrait ratio of correlations (HTMT) to assess criterion discriminant validity in independent variables (Henseler et al., 2015), or by the utilisation of mediating and moderating variables (MacKinnon, 2011). Doing so will open new avenues for research in terms of business and model driver and firm performance and value creation. Future research could test the non-crises period to understand how technology MNEs prepare for future crises.

Data availability

Data will be made available on request.

Appendix 1. Sample Characteristics

Country	Firm-Specific Characteristics	Number
Japan	AI and Digital Driven- High Tech firms	28
USA	AI and Digital Driven- High Tech firms	10
United Kingdom	AI and Digital Driven- High Tech firms	5
Germany	AI and Digital Driven- High Tech firms	5
China	AI and Digital Driven- High Tech firms	4
India	AI and Digital Driven- High Tech firms	3
Slovakia	AI and Digital Driven- High Tech firms	1
Total		56

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