Organizational resilience under COVID-19: the role of digital technology in R&D investment and performance

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Abstract

Purpose – This study aims at the sudden outbreak of COVID-19, which had an unprecedented negative impact on the Chinese economy, with firms being affected most. Firms differ in terms of their specific internal environment, shaping their ability to respond to the outbreak, so the impact may also vary.

Design/methodology/approach – In this paper Chinese listed firms are selected as samples to investigate the mediating effect of prior digital technology on the relationship between R&D (research and development) investment (funds and staff) and firm performance during the epidemic. Firm size and diversification are then introduced as moderating variables to explore the conditional mediating effect of digital technology.

Findings – The results indicate that the higher the firm’s prior R&D investment, the higher its digital technology level, and thus the stronger its resistance to the epidemic. Moreover, compared with large-scale firms, small-scale firms have the advantage of strategic flexibility to technological changes, which can help them accumulate experience from R&D activities for digital transformation, thus attenuating the negative impact of the COVID-19 on firm performance. Finally, the results also show that digital technology mediates more strongly between R&D investment and firm performance in diversified firms than in centralized firms.

Originality/value – The study builds a mediation model to reveal the process mechanism through which R&D investment affects firm performance via digital technology. Firm size and diversification are then innovatively introduced as situational factors to build the moderated mediation model, which opens up a new perspective for understanding the effect of firm internal factors on the relationship between R&D investment, digital transformation and firm performance.

Keywords COVID-19, R&D funds, R&D staff, Digital technology, Firm size, Diversification

Paper type Research paper

1. Introduction

At the beginning of 2020, the sudden outbreak of COVID-19 had an unprecedented negative impact on society and the economy. The growth rate of industrial firms above the scale dropped sharply in March 2020 (Chen and Yu, 2020). Declining orders, restricted production, understaffing, excessive fixed cost burdens, supply chain disruptions and potential credit and debt risks hit firms very hard. However, the epidemic affected different types of firms differently. Some firms benefited from previous high R&D (research and development) investment intensity and gradually started their digital transformation when emerging technologies such as big data, cloud computing, the Internet of things, blockchain, artificial intelligence and 5G communication emerged (Brammer et al., 2020; Huang et al., 2020). As a result, those firms with high digitization were more resilient when the COVID-19 epidemic...
Digital technologies such as telecommuting, smart factories and digital workshops have become an advantage for some firms in traditional industries to resist the epidemic (Ai et al., 2022). For example, although 30% of the employees in the Chinese firm Kainan Health were unable to return to work during the epidemic, the order volume was still unaffected due to its smart factory. In addition, Baosteel's Shanghai Baoshan base in China, known as the “lighthouse factory,” has also shown unique advantages in this epidemic. Most existing studies have explored the advantages brought by digital technology to firms during COVID-19 from a theoretical or case perspective. To fill the gap from the empirical perspective, we utilize a sample of 7,389 listed companies in China to conduct an empirical study to ensure the objectivity and accuracy of our findings.

As they faced COVID-19, it became very urgent for firms to enhance their resilience to cope with difficulties and complete production. Kantur and Iseri-Say, 2013 argue that the concept of organizational resilience is complex and includes multiple dimensions, while also crossing different levels. One is a dynamic concept, and the other is static. The dynamic concept primarily considers organizational resilience as the process dynamically managing and redefining organizational resilience. The static concept defines the organization as a desirable trait and advocates redefining organizational resilience from different perspectives, such as desirable traits and response outcomes. Thus, firms that showed excellent performance during the epidemic will invariably have organizational resilience in the digital era. Some scholars have pointed out that organizational resilience in the digital era involves two aspects: first, the ability of an organization to withstand challenges and to use digital means to restore its original state or function; and second, the ability to transcend its original situation and use digital technology to improve and become stronger in the face of adversity (He et al., 2022; Xie et al., 2022). The former is about the short-term survival of the firm, and the latter determines its long-term development. We thus identify the degree of development of digital technology as an external manifestation of organizational resilience under COVID-19. It is further suggested that firms with more advanced digital technology are more resilient to COVID-19 – that is, they will perform better.

Most studies have explored the factors influencing firm digital transformation in terms of technology, capabilities, management and policies. For example, Machado et al. (2022) identified technologies influencing firm digital transformation such as big data and smart data, cloud computing, social media, predictive and prescriptive analytics, the internet of Things, robotics, 3D printing and mobile technology. Some scholars have also argued that firms need a combination of capabilities to achieve digital transformation (Ellstrom et al., 2022). Wrede et al. (2020) have pointed out that business managers must be aware of the barriers and opportunities of digital transformation. Some scholars have also considered external pressures and government policies as environmental factors influencing the process of digital transformations (Aboelmaged, 2014; Tao et al., 2018). However, this literature ignores the impact of R&D investment on digital transformation. R&D investment activities are the source of organizational learning and enhanced technological capabilities (Kane and Alavi, 2007). Thus, we consider that organizational learning ability and technical capabilities facilitate firms’ integration of digital technology resources and equip a firm with the digital technologies best suited to its current environment. For example, we find that the rich R&D input activities of China Baosteel’s Shanghai Baoshan base have given the firm experience in embedding digital technologies (Zhang et al., 2021), which has helped it operate 24 h a day during the epidemic without multiple employees. Based on the above, this research first focuses on the impact of the accumulation of prior R&D investment activities on digital transformation, as well as the strategic flexibility of firms with high digital technologies, which can help firms withstand COVID-19 and show great performance; to date, this has been neglected in the influencing factors discussed in the digital transformation literature.

The process of R&D investment activities affecting digital transformation will also be affected by many external environmental factors. Therefore, we further explore which scenario
factors moderate the impact of R&D investment activities on digital transformation. The transformation of the results of firm R&D investment has been a popular research subject for the R&D management field. Previous research has explored the key factors affecting R&D investment and firm performance in terms of complex organizational structures, functions and operational processes; however, the impact of these factors on the relationship between R&D investment and digital technology has been neglected. For example, Kang et al. (2017) have pointed out that the transformation of the results of R&D investment is affected by the technological capabilities of the firm, while Tebourbi et al. (2020) have also considered the factors affecting the relationship between R&D investment and firm performance, such as managerial overconfidence and government ownership. Lu et al. (2020) have explored the moderating effect of executive overconfidence on the relationship between R&D investment and firm performance. Many existing studies have thus explored the moderating variables affecting the relationship between R&D investment and performance, but there has been a lack of attention to the moderating variables of the relationship between R&D investment and digital transformation. Chinese listed firms are selected as samples to determine whether firms of different sizes are affected differently by this epidemic, as, based on innovation management theory, firm size is a situational factor influencing firm decisions. Therefore, firm size is introduced as the first moderating variable to explore the relationship between R&D investment and digitization with different levels of diversification under the COVID-19 epidemic, which further affects the impact of digital technology on firm performance.

In addition to firm size, we find that diversification is also a key moderating variable affecting the relationship between R&D investment and digital transformation. Statsenko and de Zubielqui (2020) point out that, according to resource-based theory, a diversification strategy can spread business risks and diversified firms can establish an effective internal capital market that can break through the constraints of the external capital market. However, Andreou et al. (2016) and Sakhartov (2017) have argued that a diversification strategy will disperse the limited resources to different business units, crowding out R&D investments. As a result, current research has not reached a consensus on whether diversification is beneficial or detrimental to firms. In the particular context of COVID-19, however, we find that diversified firms have performed better than centralized firms. Based on the above, we argue that many firms have eased the pressure through diversification strategies under COVID-19. When COVID-19 occurred, the premium performance of diversified firms was more pronounced than the discount performance. Therefore, firm diversification is introduced as another situational variable to explore the impact of R&D investment on digital technology for firms with different levels of diversification under the COVID-19 epidemic, which further affects the impact of digital technology on firm performance.

This study extends research on the relationship between R&D investment, digital transformation and firm performance in two major dimensions. First, it is the first attempt to uncover the procedural mechanisms by which digital technology modulates the relationship between R&D investment and firm performance. The direct impact of R&D investment on firm performance has been extensively studied, so this study builds a mediation model to provide insight into the indirect impact of R&D investment on firm performance through digital technologies. Second, this study innovatively introduces firm size and diversification as situational factors, which opens up a new perspective for understanding the effect of firm internal factors on the relationship between R&D investment, digital transformation and firm performance.

2. Theoretical background and research hypothesis

2.1 Theoretical background

2.1.1 Innovation theory. Innovation theory was first proposed by Schumpeter, who defined innovation as the creation of a new production function – that is, a new combination of factors
of production implemented by the entrepreneur, including introduction of a new product, adoption of a new production method, opening of new markets, obtaining new sources of supply for raw materials or semi-finished products, or establishment of a new form of business organization (Schumpeter, 1911). Innovation is a kind of thinking: R&D is an act. Based on innovation theory, this research argues that a firm’s preliminary R&D investment activities provide the firm with the preliminary experience accumulation to cope with the COVID-19 epidemic. R&D investment activities provide firms with a certain reserve of technological knowledge, helping them to select projects that are suitable for their own environment from among many digital technologies, to explore the potential value of digital technologies and to promote their innovative use. Since the introduction of Schumpeter’s innovation theory, the influence of internal factors on R&D investment has received extensive attention from scholars (Sciascia et al., 2015; Tsao et al., 2015; Kang et al., 2017; Cho and Lee, 2020). Therefore, based on innovation theory, the first typical internal factor of a firm is introduced as a moderating variable—that is, firm size—to explore the impact of prior R&D investment on digitization and firm performance for firms of different sizes under the COVID-19 epidemic.

2.1.2 Resource-based theory. Resource-based theory can be traced back to Penrose’s book, The Theory of the Growth of the Firm, which argues that a business is a collection of resources and that business growth depends on the organization’s access to and application of resources (Penrose, 1959). Resources and capabilities are the two core concepts of the resource-based view. Wernerfelt (1984) broadly considers that anything that gives a firm an advantage or disadvantage can be considered a resource. The advantages and disadvantages of diversification strategies have been debated by academics. Resource-based theory suggests that the diversification strategy can spread business risks, and diversified firms can establish an effective internal capital market that can break through the constraints of the external capital market (Statsenko and de Zubielqui, 2020). This paper therefore introduces diversification as a second moderating variable based on resource-based theory to explore the different effects of prior R&D investment on digitization and firm performance for firms with different degrees of diversification under the COVID-19 epidemic.

2.1.3 Risk management theory. Risk management moved from experience to science with the use of probability theory and mathematical statistics in the 1960s. The objects of traditional risk management are mainly credit and financial risk, and the basic method in this model is risk avoidance and transfer. With the rapid changes in the socio-economic environment, enterprise risk management entered the stage of modern risk management after the 1980s, and increasing numbers of scholars and corporate management have paid attention to the holistic nature of risk management; disaster shocks accordingly entered the risk management perspective (Sahebjamnia et al., 2015). Due to the high degree of uncertainty and uniqueness of the occurrence, evolution and hazards of sudden disaster events, the risk management for the traditional emergency response model lacks a regular mechanism and neglects disaster recovery and continuity planning, which prevents enterprises from achieving reasonable and effective resource allocation between recovery and continuity planning, and even aggravates the degree of damage and prolongs recovery time. Therefore, based on risk management theory, this paper explores the ability of firms to cope with major emergencies in terms of R&D investment and digitization in conjunction with internal factors.

2.1.4 Organizational resilience theory. In 1988, Wildavsky first applied the concept of resilience to the organization. In the late 1990s, the concept of resilience began to be applied to crisis management, disasters and high-reliability organizations (Paton and David, 2001). Linkov and Trump (2019), in The Science and Practice of Resilience, provide a very systematic and detailed introduction to resilience, including the similarities and differences between risk and resilience, and explore the functions of resilience in both time and space. Wood et al. (2019) build on prior risk management research with the goal of demonstrating an approach
to measuring alignment of resilience initiatives across a large organization by considering the missions of its subcomponents. After the outbreak of the pandemic, Linkov et al. (2021) have also systematically summarized studies related to systemic risk and resilience under COVID-19.

The main reason for the lack of a clear and uniform definition of the concept of organizational resilience in academia is the differences in perspectives within organizational resilience research. Existing studies have mainly explored the concept of organizational resilience from the perspectives of capability, process and outcome (Valero et al., 2015; Duchek et al., 2019). However, all three perspectives share one essential characteristic, which is that they emphasize not only organizational resilience, but also organizational flexibility, improvisation and improvement of the ability to adapt to the environment. The focus of this paper is thus on organizational flexibility, improvisation and the ability to adapt to the environment from a digital capability perspective. Under the COVID-19 epidemic, organizational resilience in the digital era has two meanings: first, the organization should have the ability to withstand the blow and use digital means to restore its original state or function; and second, the organization should have the ability to transcend the original state and improve and get stronger in the face of adversity with the help of digital technology. This paper focuses on organizational resilience in the digital era – that is, the digital capability of the firm. The results reveal that firms with a high degree of digitization are more capable of coping with the COVID-19 epidemic, as evidenced by the fact that their performance is less negatively affected during the epidemic, and some firms with a high degree of digitization even show excellent performance.

2.2 Research hypothesis

2.2.1 Effect of R&D investment on firm performance. Existing studies have long tried to explore the relationship between R&D investment and firm performance, but the results remain inconclusive. Some studies have argued that R&D investment activities can enhance competitive advantage and promote long-term development and technological progress (James and McGuire, 2016). They believe in a positive relationship between R&D investment and firm performance (Eberhart et al., 2004). For example, Eberhart et al. (2004) argue that R&D investment activities improve long-term business performance and that this relationship is moderated by country-level factors. Vithessonthi and Racela (2016) find that R&D intensity is positively related to firm value using a sample of all nonfinancial firms listed on the United States (US) stock exchanges in the period 1990–2013. However, some scholars have found a negative relationship between R&D investment and firm performance. Chan et al. (2001) argue that R&D investment is detrimental to performance, although Knecht (2013) finds that although current R&D investment hurts the current year’s performance, it can improve future performance. In line with this, Natasha and Hutagaol (2009) find that R&D investments harm current profits, but have a positive impact on profits two years later.

When major public health emergencies occur, the market environment changes. Firms need to adjust the commodity and channel structure, as well as the marketing mode in advance to adapt to changes in the market environment that have already occurred or may occur. Continuing to follow the marketing system from before, the epidemic indicates that a firm is afraid that it cannot adapt to the changes in the market environment brought about by the epidemic. Existing studies have argued that R&D investment activities are beneficial for firms to enhance organizational learning, knowledge absorption and technological capabilities (Saarikko et al., 2020). The organization’s capability to learn, absorb knowledge and use technology can improve its ability to engage in comprehensive control and social resource integration when facing risks (Ghasemzadeh et al., 2021; Migdadi, 2021). Only firms with high comprehensive control and social resource integration capabilities can
quickly adapt to changes in the market and minimize the negative impact of unexpected events, as well as identifying market opportunities from the crisis (Orth and Schuldis, 2021). When firms face hardships, such as the mobility control, delayed resumption of work and production, and decreased sales due to the COVID-19 epidemic in 2020, prior R&D investment activities represent advantages. Comprehensive control and social resource integration capability accumulated in previous R&D investment activities can provide support for the emergency response reaction. Thus, this paper explores the effects of prior R&D investment on firm performance:

\[ H1a. \] The scale of R&D funds has a positive effect on firm performance.

\[ H1b. \] The number of R&D staff has a positive effect on firm performance.

2.2.2 The mediating role of digitization between R&D investment and firm performance. Big data, cloud computing, artificial intelligence and other digital technologies have changed the way firms operate. For example, digital production is emerging in manufacturing; online e-commerce platforms and digital marketing are emerging in retail; and online payment is emerging in finance (Hayes and Kelliher, 2022; Luangrath et al., 2022). All industries have thus started investing more in R&D to promote continuous innovation and enhance firm digitization with high R&D investment. For example, during the 2020 epidemic, Chinese company Liangxin Electric’s revenue did not decrease but rather increased by 47.98% year on year. In the face of an uncertain external environment, Liangxin Electric’s high prior R&D investment activities accelerated the pace of digital transformation. As a result, the business achieved counter-trend growth under COVID-19, demonstrating great explosive power and growth. However, the value conversion of knowledge is a complex process, especially for digital technologies (Tsou and Chen, 2021; Usai et al., 2021). Investments in digital technologies do not always yield the same returns (Usai et al., 2021). R&D investment activities can thus help firms obtain more potential value from digital technologies; they may also be a source of organizational learning, and Kane and Alavi (2007) argue that organizational learning facilitates the integration of firms’ information technology resources. Digital technology is a further upgrade of information technology; therefore, the more firms that invest in R&D activities, the better their ability to learn and absorb digital technologies, which facilitates the value conversion of related investment. Introducing and effectively integrating digital technology with existing knowledge is a complex process. R&D investment activities can enhance a firm’s technical capabilities and help the firm effectively process and integrate its internal knowledge, thus promoting the innovative use of digital technologies (Berchicci et al., 2016). As a result, firms that invest more in R&D are better able to identify digital technologies that fit their current external and internal environment and discover the potential value of more digital technologies.

In 2020, COVID-19 harmed all aspects of China’s economy and society. Both supply and demand fell sharply at the macro-level. At the micro-level, transportation, living and service industries limited the resumption of work and production of firms. Firms with high digital technology – such as telecommuting, digital retail, digital workshops, and other technologies – are, however, far less affected than others (Boeing and Wang, 2021). Compared to the severe acute respiratory syndrome (SARS) epidemic in 2003, COVID-19 is more contagious and longer-lasting (Boulos and Geraghty, 2020). Subjectively and logically, the impact of this epidemic on the Chinese economy should be even deeper; however, data released by China’s National Bureau of Statistics show that when SARS occurred in 2003, the index of the worst-affected tertiary sector, such as retail, hotel, tourism and catering, fell significantly as it operated mainly offline (Boulos and Geraghty, 2020). The COVID-19 epidemic in 2020 also affected the tertiary sector; however, due to the rapid development of digital technologies, teleconferencing, digital workshops and online
consumption scenarios became popular, which have undoubtedly become the most effective way for those retail firms to save themselves (Boeing and Wang, 2021). As a result, the tertiary sector, which already accounts for more than half of the annual gross domestic product (GDP), has a greater capacity to withstand major public health emergencies (Boulos and Geraghty, 2020; Liu et al., 2020). Some epidemic prevention measures, including home segregation, traffic restrictions and delayed start of school and return to work, also increased self-directed disposable time, so many restaurants shifted their focus to take-out business, increased live-streaming e-commerce and increased the use of logistics and warehouse robots, all of which have acted as catalysts to enhance supply-side digitization (Liu et al., 2020; Li, 2021). Digital technology is thus a lifesaver for firms in public health emergencies, and the higher the level of digital technology, the less the impact on the firm (Klein and Todesco, 2021). In summary, this research finds that, in the digital economy, R&D investment activities can enhance firms’ ability to resist major public health emergencies by ensuring digital technologies are effectively embedded. Based on the above, the following hypotheses are proposed.

H2a. Under the COVID-19 epidemic, digital technology mediates the role between the scale of R&D funds and firm performance.

H2b. Under the COVID-19 epidemic, digital technology mediates the role between the number of R&D staff and firm performance.

2.2.3 The moderating effect of firm size on the mediating role of digitization. Firm size is the intra-organizational factor influencing organizational decision-making and is a key contextual variable in innovation management research (Lahiri and Narayanan, 2013). Because it relates to the potential complexities associated with the pursuit of management innovation in organizations of different sizes, existing studies usually use the number of employees or total assets to measure firm size (Hutchinson et al., 2010; Lahiri and Narayanan, 2013). R&D investment activities can help firms gain experience in selecting the digital technologies best suited to their current environment, thus enhancing their resistance to the crisis posed by public health emergencies. However, not all firms with high R&D investment have seen such an impact. This research thus introduces intraorganizational factors as situational variables to explore the mediating roles of digital technology between R&D investment activities and firm performance for large- and small-scale firms. Existing studies show that large firms have more redundant resources for R&D innovation and are more predictive of R&D investment activities, while the higher innovation risk of small firms can lead to uneven returns (Khan et al., 2009). McDermott and Prajogo (2012) also argue that firm size and breakthrough innovation are positively correlated, because large firms have more R&D staff to accumulate more technical knowledge and capabilities, which facilitates the translation of the results of R&D investment.

However, Uhlaner et al. (2013) find that the R&D investment activities of small-scale firms can achieve better results than those of large-scale firms. When major emergency public health events occur, small-scale firms exhibit flexibility that large firms do not have. The benefits of strategic flexibility appear in the ability of firms to adjust their strategies in time to meet customer needs promptly when the environment changes (Crick et al., 2021). Some large-scale firms in China have also been caught in the resource mismatch trap. Although the scale of the firms is large, their productivity level is low, which can also lead to a low conversion rate for R&D investment, as the actual input and output are not proportional (Huang et al., 2015). The lack of accumulation of prior experience, organizational learning ability and technical capability can lead firms to fall into the digital trap when introducing digital technologies. For example, digital technology has been slow to spread across large firms, and although many firms have developed digital technologies such as flexible manufacturing and mass customization, they are not the mainstream mode of internal operation.
This research therefore argues that the conversion rate of R&D investment is higher in small-scale firms in China, which have accumulated more experience in the implementation of digital technology. Moreover, small-scale firms are more accurate and sensitive to capturing new technologies, and the cost of digital transformation is lower and more efficient. In contrast, large-scale firms have more complex organizational features and richer resources, resulting in slower insight and action on technological innovation. Thus, firm size inversely moderates the mediating role of digital technology between R&D investment and firm performance. Based on the above, the following hypotheses are proposed.

\[ H3a. \] The mediating effect of digital technology between the scale of R&D funds and firm performance is inversely moderated by firm size.

\[ H3b. \] The mediating effect of digital technology between the number of R&D staff and firm performance is inversely moderated by firm size.

2.2.4 The moderating effect of diversification strategy on the mediating role of digitization. Diversification of resource structure is another situational factor that affects the conversion of R&D investments into results (Baysinger and Hoskisson, 1989; Banker et al., 2011). There has been no consensus in the research on the impact of diversification on firms. According to market power theory, the fundamental reason why diversified firms operate better than centralized ones is that diversified firms are more likely to have access to the corresponding market power (Matvos et al., 2018). For example, Statsenko and de Zubielqui (2020) find that service and market diversification positively mediate the relationship between customer collaboration and innovation performance through a case study of 156 mining equipment, technology and service firms in South Australia. Linkov et al. (2022) combine this with COVID-19 and point out that COVID-19 has affected all forms of global international engagement, including both long-standing and recently formed research teams, and diversity and inclusiveness is a requirement for resilient ecological systems. However, principal-agent and management cost theories have a negative attitude toward diversification. Yang et al. (2021) conduct an empirical study using a sample of listed companies in the Chinese stock market between 2003 and 2017 and find that diversification reduces cash dividend payments. Andreou et al. (2016) also find that diversification reduces shareholder wealth in a sample of all firms in the Compustat industrial sector between 1998 and 2008.

Diversified firms require more coordination and control than centralized firms due to their broader scope of operation (Baysinger and Hoskisson, 1989; Berrill et al., 2021). Diversified firms are thus more dependent on digital technologies and can benefit more from high R&D investments (Bernot et al., 2021). During the COVID-19 epidemic, diversification somewhat spread out the business risks. When the external environment is stable, diversified operations crowd out the R&D investment of the main business, which is disadvantageous to firm development. However, when major public health emergencies occur, the negative impact becomes an opportunity. As the Chinese saying goes, “if the East does not shine, the West does not shine”: epidemics do not affect all sectors, so decentralized prior investments are advantageous in this case (Chari et al., 2008; Lee et al., 2020). This resilience varies from industry to industry. For example, demand increased in the pharmaceutical, detergent and food industries during the outbreak. Some manufacturers of automobiles, household appliances and cell phones started producing masks. In the first two months of 2020, more than 3,000 firms in China added masks, protective clothing, disinfectants, thermometers and medical equipment to their operations. Many firms did not initially sell these medical supplies on the market but rather offered them as donations. Thus, they not only gained a social and brand effect, but also expanded production to make up for losses in their main business.

Diversified firms investing in different types or sectors can effectively reduce nonsystematic risks and gain more heterogeneous information from other sectors
(Ji et al., 2020). When COVID-19 appeared, many diversified firms made timely strategic adjustments. In the current digital economy, diversified firms have multiple business units to coordinate. The demand of diversified firms for digital technologies is thus even greater (Stern and Henderson, 2004). Firms can enhance their organizational learning ability and accumulate technical knowledge by increasing R&D investment activities, so firms can select the digital technologies that best fit their current environment from the vast array available. This is more beneficial for diversified firms with more complex internal and external systems than for centralized firms. Based on the above, this research argues that the R&D investment activities of diversified firms have a greater positive impact on firm performance through digital technologies under sudden public health events than those of centralized firms:

\[ H4a. \quad \text{The mediating effect of firms' digital technology between the scale of R&D funds and firm performance is positively moderated by diversification.} \]

\[ H4b. \quad \text{The mediating effect of firms' digital technology between the number of R&D staff and firm performance is positively moderated by diversification (see Figure 1 below).} \]

The theoretical model of the hypotheses is as follows.

### 3. Research design
#### 3.1 Data
Listed firms in China’s Shanghai and Shenzhen markets in 2019 and 2020 are selected as the samples. The selection principles are as follows: (1) excluding listed financial firms; (2) excluding listed firms with a gearing ratio greater than 1; (3) the selected sample firms must disclose information by industry or distinguish operating income by industry in their annual reports; (4) excluding firms that were special treatment (ST) (listed companies that have been losing money for two consecutive years and are subject to special treatment) and particular transfer (PT) (if a listed company has suffered losses for three consecutive years, its shares will be suspended from listing, and the exchange will implement special transfer services for such suspended stocks) for two consecutive years during the study period; and (5) excluding firms with serious missing financial data in the database. Sample data are obtained from the Wind financial database, which yields 7,389 sample firms after screening according
to the above principles and the China Stock Market & Accounting Research Database (CSMAR) database, which is the first and largest accurate database of financial and economic information in China, and the only Chinese database included in the Wharton research service system by the Wharton School at the University of Pennsylvania in the US. Because the effects of R&D investment activities and digital technology on firm performance are lagged, this paper selects data from 2020 to measure firm performance, and data from 2019 to measure other research variables.

3.2 Measurement of variables

(1) Independent variables. The scale of R&D funds and the number of R&D staff are used to measure R&D investment. In existing studies, the scale of R&D funds is measured by the ratio of R&D investment to operating revenue, and the number of R&D staff is measured by the ratio of R&D staff to all employees (Choi et al., 2015; Cho and Lee, 2020; Tebourbi et al., 2020; Yuan and Nishant, 2021). This paper obtains these data from the 2019 R&D innovation section of the CSMAR database for listed firms.

(2) Dependent variable. Tobin’s Q is used to measure firm performance. Tobin’s Q is the ratio of the market value of a firm to the replacement cost of capital. Its economic meaning is to compare whether the market value of an enterprise as an economic subject is greater than the cost of capital that brings cash flow to the firm. When the COVID-19 epidemic occurred, the ability of firms to cope with the epidemic had gradually accumulated in the past production and operation. Therefore, this research considers that the previous R&D investment and digital technology affect firm performance in the year of the epidemic – that is, the impact of R&D investment and digital technology on firm performance is subject to hysteresis, so the Tobin’s Q value for the year 2020 is used; Tobin’s Q is also a market performance indicator, which is more difficult to manipulate than financial performance indicators. Studies related to R&D investment and technological innovation widely uses Tobin’s Q as a dependent variable.

(3) Mediating variable. The 2019 years-end balance of items related to computer software, information, systems, digitization, platforms and cloud-related technologies in the breakdown of intangible assets from the financial statements of firms as a percentage of the total year-end intangible assets are used to measure digital technology (Porter and Heppelmann, 2014; Shuchuna et al., 2021).

(4) Moderating variables. First, the natural logarithm of the firm’s total assets is used to measure firm size. Total assets include everything owned or controlled by the firm, including current assets, long-term investments, fixed assets, intangible assets, deferred assets, other long-term assets and deferred taxes, and are the total assets on the firm’s balance sheet (Dass, 2000; Munjal et al., 2019). This can be a good measure of the richness of a firm’s resources. Second, there are various ways to measure diversification. This research uses the industry classification guidelines issued by the China Securities Regulatory Commission in 2001 as the basis, combined with the operating income by industry disclosed in the financial reports of sample firms, and summarizes the operating income of firms according to different industries. The proportion of the operating income of firms in different industries occupying the total operating income is then calculated. Finally, the industry classification revenue whose proportion is greater than 10% is then selected and the revenue entropy index is calculated to measure the degree of diversification (Dass, 2000; Lins and Servaes, 2002).
Control variables. Concerning existing studies and the research needs, balance sheet ratio, firm growth and firm age are selected as control variables. Gearing represents a firm’s attitude toward debt, and financial leverage affects firm performance. Firm age is measured by the natural logarithm of the year from the firm’s inception to the year of the study (Li et al., 2008). The growth rate of the firm’s main business revenue is used to measure firm growth (Ho et al., 2011).

4. Results
4.1 Descriptive statistical analysis and correlation analysis
Table 1 shows the descriptive statistical analysis of the variables. The scale of R&D funds is measured by the ratio of R&D investment to operating revenue, and the number of R&D staff is measured by the ratio of R&D staff to all employees. The mean value of R&D funds is 5.299, and the mean value of R&D staff is 17.039% according to 7,389 sample companies. This indicates that the level of R&D investment among Chinese listed companies is not high. The mean value for digitization level is 0.142, which indicates that the digital transformation of Chinese listed companies is at the initial stage. Table 2 shows the correlation analysis between the variables. The correlation coefficients between R&D funds and R&D staff size and Tobin’s Q are 0.265 and 0.233, respectively, which are significantly correlated at the 0.01 level. This indicates that there is a positive and significant relationship between both R&D funds and R&D staff and Tobin’s Q. The variance inflation factor (VIF) has an empirical value of 10. If the VIF of the independent variables is greater than 10, it means that the model has a multicollinearity problem. The bootstrap sampling method is used to test the VIF of the independent variables. The results in Table 2 show that the VIF values of the independent variables are all less than 2, which indicates that there is no multicollinearity problem.

4.2 Analysis of hypothesis testing results
4.2.1 Basic regression and mediating effect of digital technology. Table 3 shows the relationship between R&D funds and firm performance; digital technology plays a mediating role. Model 1 shows that there is a significant and positive relationship between R&D funds and Tobin’s Q ($\beta = 0.079, p < 0.01$), so hypothesis H1a is supported. Stepwise regression is used to test the mediating role of digital technology. Model 2 shows that there is a significant and positive relationship between digital technology and Tobin’s Q ($\beta = 0.846, p < 0.01$). Model 3 shows that there is a significant and positive relationship between R&D funds and digital technology ($\beta = 0.012, p < 0.01$). This suggests that digital technology mediates the relationship between R&D funds and Tobin’s Q. To visualize the mediating role of digital technology, bootstrapping is combined with Sobel’s test to set a 1,000 sample size criterion at

<table>
<thead>
<tr>
<th>Variables</th>
<th>N</th>
<th>Mean</th>
<th>Std</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tobin Q</td>
<td>7,389</td>
<td>2.215</td>
<td>1.916</td>
<td>0.666</td>
<td>30.568</td>
</tr>
<tr>
<td>R&amp;D funds</td>
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<td>5.299</td>
<td>5.362</td>
<td>0</td>
<td>83.23</td>
</tr>
<tr>
<td>R&amp;D staff</td>
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<td>17.039</td>
<td>14.091</td>
<td>0</td>
<td>91.76</td>
</tr>
<tr>
<td>Digital technology</td>
<td>7,389</td>
<td>0.142</td>
<td>0.213</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Firm size</td>
<td>7,389</td>
<td>22.192</td>
<td>1.198</td>
<td>19.114</td>
<td>27.051</td>
</tr>
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<td>Diversification</td>
<td>7,389</td>
<td>0.349</td>
<td>0.432</td>
<td>0</td>
<td>2.187</td>
</tr>
<tr>
<td>Growth</td>
<td>7,389</td>
<td>0.164</td>
<td>0.899</td>
<td>-0.913</td>
<td>28.573</td>
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<td>Firm age</td>
<td>7,389</td>
<td>2.972</td>
<td>0.277</td>
<td>1.609</td>
<td>4.788</td>
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<td>Lev</td>
<td>7,389</td>
<td>0.407</td>
<td>0.199</td>
<td>0.008</td>
<td>2.849</td>
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Table 1. The descriptive statistical analysis
<table>
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<th>Variables</th>
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<th>4</th>
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<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>VIF</th>
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<tbody>
<tr>
<td>1 Tobin Q</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 R&amp;D funds</td>
<td>0.265***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 R&amp;D staff</td>
<td>0.233***</td>
<td>0.655***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Digital technology</td>
<td>0.105***</td>
<td>0.283***</td>
<td>0.354***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Firm size</td>
<td>-0.245***</td>
<td>-0.218***</td>
<td>-0.193***</td>
<td>-0.076***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 Diversification</td>
<td>-0.137***</td>
<td>-0.018</td>
<td>-0.003</td>
<td>-0.025**</td>
<td>0.156***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7 Growth</td>
<td>0.055***</td>
<td>-0.032***</td>
<td>0.015</td>
<td>0.048***</td>
<td>-0.001</td>
<td>-0.017</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8 Firm age</td>
<td>-0.083***</td>
<td>-0.124***</td>
<td>-0.108***</td>
<td>-0.047***</td>
<td>0.153***</td>
<td>0.115***</td>
<td>0.027**</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9 Lev</td>
<td>-0.233***</td>
<td>-0.222***</td>
<td>-0.186***</td>
<td>-0.022*</td>
<td>0.443***</td>
<td>0.101***</td>
<td>0.038**</td>
<td>0.077***</td>
<td>1</td>
<td>1.01</td>
</tr>
</tbody>
</table>

**Note(s):**  
\( n = 7,389, \) *\( p < 0.1, ** p < 0.05, *** p < 0.01 \)
95% confidence interval and obtain the confidence interval for bias correction (LLCI = 0.001, ULCI = 0.006), excluding 0. The above analysis indicates that digital technology plays a partially mediating role between R&D funds and firm performance, so hypothesis $H_2a$ is supported.

Table 4 shows the relationship between R&D staff and firm performance and the mediating role of digital technology. Model 5 shows a significant positive relationship between R&D staff and Tobin’s Q ($\beta = 0.026, p < 0.001$), so hypothesis $H_1b$ is supported. Model 6 shows a significant positive relationship between digital technology and Tobin’s Q ($\beta = 0.846, p < 0.001$), and model 7 shows a significant positive relationship between R&D staff and digital technology ($\beta = 0.006, p < 0.001$). The result indicates that digital technology mediates the relationship between R&D staff and Tobin’s Q. The mediating role of digitization technology is then tested using a combination of bootstrapping and the Sobel
test, obtaining the bias-corrected confidence interval \( \text{LLCI} = 0.0005 \) \( \text{ULCI} = 0.003 \), which
does not contain 0. The above analysis indicates that digital technology plays a partially
mediating role between R&D staff and firm performance, so hypothesis H2b is verified.

4.2.2 Moderating effects of firm size on the mediating role of digital technology. The
moderating effect of firm size is examined through a combination of structural equation
modeling (SEM) and the bootstrap sampling method. Model 9 in Table 5 shows that the
interaction term of R&D funds and firm size is negatively related to digital technology
\( \beta = -0.017, p < 0.01 \), which indicates that firm size inversely moderates the relationship
between R&D funds and digital technology.

To visualize the moderating effect of firm size on the mediating role of digital technology
between R&D funds and firm performance, one standard deviation is added or subtracted from
the mean firm size; then, a 1,000-sample regression is performed with the bootstrap resampling
method. The results show that, at the 95% confidence interval, there is no mediating effect of
digital technology between R&D funds and firm performance for large firm size (mean plus one
standard deviation) – that is, the deviation correction confidence interval contains 0 \( \text{LLCI} = -
0.0045, \text{ULCI} = 0.0011 \). However, at small (mean minus one standard deviation) and
intermediate (mean) firm sizes, there is a mediating effect of digital technology between R&D
funds and firm performance – that is, the bias-corrected confidence interval does not contain
0 \( \text{LLCI1} = 0.0018, \text{ULCI1} = 0.0139; \text{LLCI2} = 0.0008, \text{ULCI2} = 0.0053 \); as firm size increases, the
mediating effect of digitization weakens \( 0.0079 > 0.0031 \).

The independent variable of R&D staff is analyzed as above. The result shows that the
interaction term of R&D staff and firm size is negatively correlated with digital technology
\( \beta = -0.029, p < 0.001 \). One standard deviation from the mean value of firm size is then added or
subtracted, and a 1,000-sample regression is performed with the bootstrap resampling method.
The results show that the bias-corrected confidence interval contains 0 \( \text{LLCI} = -0.0093,\)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Digital technology M9</th>
<th>Tobin Q M10</th>
<th>Digital technology M11</th>
<th>Tobin Q M12</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D funds</td>
<td>0.010*** (0.0005)</td>
<td>0.070*** (0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D staff</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm size</td>
<td>-0.009*** (0.002)</td>
<td>-0.220*** (0.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D funds * Firm size</td>
<td>-0.017*** (0.003)</td>
<td>0.013 (0.025)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D staff* Firm size</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Digital technology</td>
<td>0.289*** (0.103)</td>
<td>0.198* (0.106)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Growth</td>
<td>0.013*** (0.003)</td>
<td>0.139*** (0.023)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm age</td>
<td>-0.010 (0.009)</td>
<td>-0.195** (0.076)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lev</td>
<td>0.053*** (0.013)</td>
<td>-1.225*** (0.118)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Bootstrap indirect effect test results

<table>
<thead>
<tr>
<th>Independent variable: R&amp;D funds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low firm size</td>
</tr>
<tr>
<td>Medium firm size</td>
</tr>
<tr>
<td>High firm size</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent variable: R&amp;D staff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low firm size</td>
</tr>
<tr>
<td>Medium firm size</td>
</tr>
<tr>
<td>High firm size</td>
</tr>
</tbody>
</table>

Table 5. The moderating effect of firm size on the mediating role of digital technology

Note(s): LLCI, ULCI denote the lower and upper bound of 95% confidence interval, respectively, and standard
deviation is in parentheses

*p < 0.1, **p < 0.05, ***p < 0.01
ULCI = 0.0004) for large firm sizes, but at low and intermediate levels, the bias-corrected confidence interval does not contain 0 (LLCI1 = 0.0001, ULCI1 = 0.0135; LLCI2 = 0.0004, ULCI2 = 0.0019). The mediating role of digital technology weakens as firm size increases (0.0068 > 0.0010). The above analysis indicates that the mediating effect of firm size on the degree of digitization plays an inverse moderating role; the above analysis also shows that firm size reversely moderates the mediating effect of digital technology on the relationship between R&D funds, R&D staff and firm performance. It is thus assumed that H3a and H3b are supported.

4.2.3 Moderating effects of diversification on the mediating role of digital technology. The moderating effect of diversification is also tested by a combination of SEM and bootstrap sampling, and the results are shown in Table 6. Model 13 shows that the interaction term of R&D funds and diversification is positively related to digital technology ($\beta = 0.011$, $p < 0.001$). Model 15 shows that the interaction term of R&D staff and diversification is positively related to digital technology ($\beta = 0.008$, $p < 0.001$). This indicates that diversification positively moderates the relationship between R&D investment (funds and staff) and digital technology.

To visualize the moderating effect of diversification on the mediating role of digital technology on the relationship between R&D investment and firm performance, one standard deviation from the mean of diversification is added and subtracted, and a 1000-sample regression is performed by the bootstrap resampling method. The results indicate that the mediating effect of digital technology on the relationship between R&D funds and firm performance is not significant as the 95% confidence interval for a low level of diversification (mean minus one standard deviation) contains 0 (LLCI = -0.0024, ULCI = 0.0027). The mediating effect of digital technology on the relationship between R&D staff and firm performance is also not significant – that is, the bias-corrected confidence interval contains 0 (LLCI = -0.0029, ULCI = 0.0031). However, at both the

<table>
<thead>
<tr>
<th>Variables</th>
<th>Digital technology M13</th>
<th>Tobin Q M14</th>
<th>Digital technology M15</th>
<th>Tobin Q M16</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D funds</td>
<td>0.012*** (0.0005)</td>
<td>0.077*** (0.004)</td>
<td>0.005*** (0.0002)</td>
<td>0.025*** (0.002)</td>
</tr>
<tr>
<td>R&amp;D staff</td>
<td>0.011*** (0.0002)</td>
<td>-0.065*** (0.020)</td>
<td>0.008*** (0.002)</td>
<td>-0.084*** (0.021)</td>
</tr>
<tr>
<td>Firm size</td>
<td>-0.012*** (0.006)</td>
<td>-0.481*** (0.049)</td>
<td>-0.013** (0.005)</td>
<td>-0.491*** (0.049)</td>
</tr>
<tr>
<td>R&amp;D funds * diversification</td>
<td>0.011*** (0.002)</td>
<td>-0.065*** (0.020)</td>
<td>0.008*** (0.002)</td>
<td>-0.084*** (0.021)</td>
</tr>
<tr>
<td>R&amp;D staff * diversification</td>
<td>0.011*** (0.002)</td>
<td>-0.065*** (0.020)</td>
<td>0.008*** (0.002)</td>
<td>-0.084*** (0.021)</td>
</tr>
<tr>
<td>Digital technology</td>
<td>0.320*** (0.103)</td>
<td>0.273*** (0.106)</td>
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<td></td>
</tr>
<tr>
<td>Growth</td>
<td>0.013*** (0.003)</td>
<td>0.141*** (0.023)</td>
<td>0.010*** (0.003)</td>
<td>0.121*** (0.023)</td>
</tr>
<tr>
<td>Firm age</td>
<td>-0.012 (0.009)</td>
<td>-0.212*** (0.076)</td>
<td>-0.007 (0.008)</td>
<td>-0.251*** (0.077)</td>
</tr>
<tr>
<td>Lev</td>
<td>0.049*** (0.012)</td>
<td>-1.684*** (0.108)</td>
<td>0.051*** (0.012)</td>
<td>-1.809*** (0.108)</td>
</tr>
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</table>

**Bootstrap indirect effect test results**

<table>
<thead>
<tr>
<th>Independent variable: R&amp;D funds</th>
<th>Coefficient</th>
<th>Boot SE</th>
<th>LLCI</th>
<th>ULCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low diversification</td>
<td>0.0001</td>
<td>0.0013</td>
<td>-0.0024</td>
<td>0.0027</td>
</tr>
<tr>
<td>Medium diversification</td>
<td>0.0037***</td>
<td>0.0013</td>
<td>0.0011</td>
<td>0.0063</td>
</tr>
<tr>
<td>High diversification</td>
<td>0.0072***</td>
<td>0.0029</td>
<td>0.0017</td>
<td>0.0126</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent variable: R&amp;D staff</th>
<th>Coefficient</th>
<th>Boot SE</th>
<th>LLCI</th>
<th>ULCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low diversification</td>
<td>-0.0008</td>
<td>0.0011</td>
<td>-0.0029</td>
<td>0.0013</td>
</tr>
<tr>
<td>Medium diversification</td>
<td>0.0015***</td>
<td>0.00065</td>
<td>0.0005</td>
<td>0.0026</td>
</tr>
<tr>
<td>High diversification</td>
<td>0.0038***</td>
<td>0.0016</td>
<td>0.0005</td>
<td>0.0070</td>
</tr>
</tbody>
</table>

**Note(s):** LLCI, ULCI denote the lower and upper bound of 95% confidence interval, respectively, and standard deviation is in parentheses

*p < 0.1, **p < 0.05, ***p < 0.01

Table 6. The moderating effect of diversification on the mediating role of digital technology
high (mean plus one standard deviation) and intermediate levels (mean) of diversification, there
digital technology has a mediating role between R&D investment (R&D funds and R&D staff) and
firm performance, and none of the deviation correction confidence intervals contain 0. With
increasing diversification, the mediating role of digital technology between R&D funds and firm
performance increases (0.0037 > 0.0072), and the mediating role of digital technology between
R&D staff and firm performance also increases (0.0015 > 0.0038). The above analysis indicates that
firm diversification plays a positive moderating role in the mediating role of digital technology on
the relationship between R&D investment (funds and staff) and firm performance. Hypotheses
H4a and H4b are thus supported.

4.2.4 Robustness test. To verify the accuracy of the above findings, this paper adds two
different control variables that may affect firm performance, return on total assets (ROA) and
return on equity (ROE), to the above models, and all the above models are regressed again.
Table 7 shows the results of the test for mediating effects. The mediating effects of digital
technology in R&D funds and firm performance and in R&D staff and firm performance
remain significant. Table 8 shows the results of the moderating effects of firm size and
diversification, which are not significantly different from the above test results.

5. Discussion and conclusion
5.1 Conclusion
This article combined innovation, resource-based, risk management and organizational
resilience theories to explore the relationship between R&D investment, digital technology
and performance under COVID-19. The findings suggest that digital technology mediates the
relationship between R&D investment and firm performance, while firm size negatively
moderates the mediating effect of digital technology and that diversification positively
moderates the mediating effect of digital technology.

5.2 Discussion
5.2.1 Theoretical significance. This study makes significant contributions to the current
scholarly literature. First, this research finds the positive effect of prior R&D investment on
firm performance when COVID-19 occurred. Most existing studies on the COVID-19 outbreak
have started from the perspective of theory and case analysis suggesting that prior R&D
investment has become an advantage for firms to resist the consequences of the crisis. This
research presents an empirical study to break through the bottleneck of existing studies and
enrich the research on the impact of major public health emergencies on firm performance.
Moreover, most previous studies on R&D investment and firm performance have been based
on normal periods of economic development and have not involved sudden changes in the
macro environment, such as those that occurred under COVID-19. Therefore, this study takes

<table>
<thead>
<tr>
<th>Bootstrap test results</th>
<th>Coefficient</th>
<th>Boot SE</th>
<th>LLCI</th>
<th>ULCI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent variables: R&amp;D funds</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect effect</td>
<td>0.006***</td>
<td>0.001</td>
<td>0.003</td>
<td>0.009</td>
</tr>
<tr>
<td>Direct effect</td>
<td>0.074***</td>
<td>0.007</td>
<td>0.059</td>
<td>0.088</td>
</tr>
<tr>
<td><strong>Independent variables: R&amp;D staff</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect effect</td>
<td>0.003***</td>
<td>0.0006</td>
<td>0.002</td>
<td>0.004</td>
</tr>
<tr>
<td>Direct effect</td>
<td>0.024</td>
<td>0.003</td>
<td>0.019</td>
<td>0.030</td>
</tr>
</tbody>
</table>

Table 7. Robustness test of the mediating effect of digitization

Note(s): LLCI, ULCI denote the lower and upper bound of 95% confidence interval, respectively
*p < 0.1, **p < 0.05, ***p < 0.01
COVID-19 as a background to explore the influence of the accumulation of firms’ previous R&D investment on their ability to cope with a shock, which not only adds a new perspective for exploring the relationship between R&D investment and firm performance but also can provide a reference for firms to optimize the investment structure of research industry.

Second, the existing literature has explored the direct relationship between R&D investment and firm performance, while the process mechanism for how R&D investment affects firm performance has remained poorly understood. This study represents one of the attempts to fill this important gap by building a mediation model to reveal the mediating role of digital technology in the relationship between R&D investment and firm performance. In the digital economy, firms are increasing their R&D investment to accelerate the pace of digital transformation in a digital innovation pattern. R&D investment activities can thus, to a certain extent, help to accumulate organizational learning and technology experience for the digital transformation of firms. When the COVID-19 outbreak occurred, firms with more advanced digital technologies were less negatively affected by COVID-19. Most of the studies on the economic contribution of digital transformation have been conducted from a macro perspective, including the industry and regional level, and there are not enough studies exploring the micro-enterprise level. This research takes firms as the research sample to increase the research perspective on digital transformation at the micro level. Moreover, most current studies on digital transformation are theoretical analyses, and in the few empirical studies, the data are mainly from questionnaires or interviews. These two methods are more targeted, but the sample source is limited and easily influenced by limitations of time, space and subjectivity. The present research adopts data from the annual and financial reports of listed companies, which expands the scope and sample size of research subjects and includes firms from different regions, industries, scales and nature, thus helping to yield richer research conclusions.

We can also highlight the unique role of firm size in our efforts to understand the performances of different firms in the face of major public health emergencies based on

<table>
<thead>
<tr>
<th>Moderator: firm size</th>
<th>Coefficient</th>
<th>Boot SE</th>
<th>LLCI</th>
<th>ULCI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent variables: R&amp;D funds</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low firm size</td>
<td>0.0133***</td>
<td>0.0036</td>
<td>0.0062</td>
<td>0.0204</td>
</tr>
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**Note(s):** LLCI, ULCI denote the lower and upper bound of 95% confidence interval, respectively. *p < 0.1, **p < 0.05, ***p < 0.01
firm-internal factors. Firm size is one of the situational factors of innovation management theory (Rothwell, 1991; Shefer and Frenkel, 2005). Accordingly, we build a moderated mediation model to reveal how firm size moderates the mediating effect of digital technology in the relationship between R&D investment and firm performance. When this epidemic occurred, firms of different sizes showed different levels of resilience. Some studies have shown that large-scale firms are more resilient to major public health emergencies than small-scale firms, but these studies tend to overlook other characteristics of large-scale firms. For example, some large-scale firms in China are caught in a resource mismatch trap. Small-scale firms, on the other hand, are characterized by strategic flexibility and instead have a sharper insight into new technologies, such as digital technologies. They are therefore better equipped to take advantage of the experience accumulated through their R&D investment activities. The results therefore strengthen the understanding of the effect of firm internal factors on the transformation of R&D investment results by finding that firm size negatively moderates the mediating effect of digital technology on the relationship between R&D investment and firm performance.

Finally and relatedly, we build on the resource-based theory that dominates the existing theoretical explanations and combine it with innovation theory in developing our final theoretical model by introducing another contextual factor in addition to firm size – namely, diversification. Existing studies have argued that diversification strategies divert resources and crowd out R&D investments (Baysinger and Hoskisson, 1989; Banker et al., 2011); however, when COVID-19 occurred, the diversification strategy represented an unprecedented advantage. As the old Chinese saying goes, “when it is dark in the East, it is light in the West, and when things are dark in the South, there is still light in the North.” The result finds that diversification positively moderates the mediating role of digital technology between R&D investment and firm performance, which is a new understanding of firm diversification strategies and enriches the research on the impact of R&D investment on outcome transformation.

5.2.2 Practical significance. The sudden outbreak of COVID-19 in 2020 posed a serious challenge to all industries and simultaneously drove digital transformation and firm change. Due to the suddenness and persistence of the outbreak, many firms did not react in time, resulting in poor communication with customers, shutdowns and plummeting sales. However, this research finds that some firms with high digital skills lost less than others. R&D investment activities thus appear able to enhance firms’ organizational learning and technical ability, which allow them to accumulate rich experience for their digital transformation and help them to select digital technologies suitable for the current production and operation environment. In this era of comprehensive digitization, firms should make more efforts to achieve online organization, coordination, production and sales. Total digitization can enhance firms’ ability to respond to emergencies. As in the case of COVID-19, firms with a high level of digitization were better able to cope, and many new digital firms have emerged. Firms should thus focus on accumulating experience in R&D investment activities, and accelerate digital transformation to promote the change and reinvention to keep up with the speed of the changing times.

Second, the results of this research show that, when COVID-19 occurred, the accumulation of experience in R&D investment activities and a high level of digital technology became tools for firms to resist the epidemic as much as possible. However, firms’ internal factors cannot be ignored. Many large-scale firms in China generally face a low conversion rate for R&D investments and are much less sensitive to new technologies such as digitization than small-scale firms. The redundant organizational structure of large-scale firms constrains digital transformation, and this vulnerability has been especially evident during this epidemic. There are many problems in the digital transformation of large-scale firms, such as digital silos, ecosystem integration and cybersecurity, so large firms not only need to establish the appropriate values and mindsets within the firm but also avoid becoming obsessed with speed at the expense of a good digital experience.
5.2.3 Limitation and future research. The first limitation is that the COVID-19 outbreak that occurred in 2020 was a sudden major public health event, and such events do not occur frequently in the course of business. Second, cross-sectional data are selected as the research sample, ignoring consideration of time series dimension; future research can thus add the time series dimension to the model. Third, Chinese listed companies are selected as the research sample, which allows a certain generalizability for other Chinese companies, but the novel coronavirus epidemic is a global public health event, so future research could further expand the sample to global companies. Finally, this research explored whether upfront R&D investment is beneficial for firms to improve their digital capabilities, and further, if firms with high digital capabilities are well positioned to withstand the impact of an epidemic, but this lacked an understanding of some metrics associated with recovery and adaptation after the pandemic. Subsequent studies can therefore further enrich the metrics associated with recovery and adaptation after COVID-19, as well as the relationship between different critical functions of organizations and different resilience metrics.

References


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